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AN ANALYTICS-BASED APPROACH TO THE STUDY OF  
LEARNING NETWORKS IN DIGITAL EDUCATION SETTINGS

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Doctor of Philosophy  
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# Abstract

Investigating how groups communicate, build knowledge and expertise, reach consensus or collaboratively solve complex problems, became one of the main foci of contemporary research in learning and social sciences. Emerging models of communication and empowerment of networks as a form of social organization further reshaped practice and pedagogy of online education, bringing research on *learning networks* into the mainstream of educational and social science research. In such conditions, massive open online courses (MOOCs) emerged as one of the promising approaches to facilitating learning in networked settings and shifting education towards more open and lifelong learning. Nevertheless, this most recent educational turn highlights the importance of understanding social and technological (i.e., material) factors as mutually interdependent, challenging the existing forms of pedagogy and practice of *assessment for learning* in online environments.

On the other hand, the main focus of the contemporary research on networked learning is primarily oriented towards retrospective analysis of learning networks and informing design of future tasks and recommendations for learning. Although providing invaluable insights for understanding learning in networked settings, the nature of commonly applied approaches does not necessarily allow for providing means for understanding learning as it unfolds. In that sense, learning analytics, as a multidisciplinary research field, presents a complementary research strand to the contemporary research on learning networks. Providing theory-driven and analytics-based methods that would allow for comprehensive assessment of complex learning skills, learning analytics positions itself either as the end point or a part of the pedagogy of learning in networked settings.

The thesis contributes to the development of learning analytics-based research in studying learning networks that emerge from the context of learning with MOOCs. Being rooted in the well-established evidence-centered design assessment framework, the thesis develops a conceptual analytics-based model that provides means for understanding learning networks from both individual and network levels. The proposed model provides a theory-driven conceptualization of the main constructs, along with their mutual relationships, necessary for studying learning networks. Specifically, to provide comprehensive understanding of learning networks, it is necessary to account for *structure* of learner interactions, *discourse* generated in the learning process, and *dynamics* of structural and discourse properties. These three elements – structure, discourse, and dynamics – should be observed as mutually dependent, taking into account learners' personal interests, motivation, behavior, and contextual factors that determine the environment in which a specific learning network develops. The thesis also offers an operationalization of the constructs identified in the model with the aim at providing learn-

ing analytics-methods for the implementation of assessment for learning. In so doing, I offered a re-definition of the existing educational framework that defines learner engagement in order to account for specific aspects of learning networks emerging from learning with MOOCs. Finally, throughout the empirical work presented in five peer-reviewed studies, the thesis provides an evaluation of the proposed model and introduces novel learning analytics methods that provide different perspectives for understanding learning networks. The empirical work also provides significant theoretical and methodological contributions for research and practice in the context of learning networks emerging from learning with MOOCs.

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# Declaration of authorship

I declare that this thesis has been composed solely by myself and that it has not been submitted, either in whole or in part, in any previous application for a degree. Except where otherwise acknowledged, the work presented is entirely my own. This thesis also includes seven peer-reviewed publications produced under the joint authorship, as detailed below.

The work presented in [Section 2.2 \(Chapter 2\)](#) was previously published in SRI Education Analytics4Learning paper series as:

[Joksimović, S., Gašević, D., Bayne, S., Hatala, M., and Dawson, S. \(2017\). Studying Learning in Nonformal Digital Educational Settings. In Measurement in Digital Environments White Paper Series, 118, SRI International, Menlo Park, CA. Retrieved from \[http://a4li.sri.com/archive/papers/Joksimovic\\\_2017\\\_Nonformal\\\_Learning.pdf\]\(http://a4li.sri.com/archive/papers/Joksimovic\_2017\_Nonformal\_Learning.pdf\).](#)

My contribution was as follows:

- Study conception and design performed most of the work (**90%**)
- Drafting the manuscript - performed all the work (**100%**)

Given that this work presents a conceptual paper, there was no data collection and analysis required. In addition to the work contributed by my supervisors, Professor [Dawson](#) also contributed (20%) in providing critical revisions to the manuscript.

The work presented in [Section 3.2 \(Chapter 3\)](#) was submitted for publication in Review of Educational Research journal as:

[Joksimović, S., Poquet, O., Kovanović, V., Dowell, N., Caitlin, M., Gašević, D., Dawson, S., Brooks, C., Graesser, A. C. \(2017, under review\). How do we Model Learning at Scale? A Systematic Review of the Literature. Review of Educational Research.](#)

My contribution was as follows:

- Study conception and design performed most the work (**85%**)
- Acquisition of data performed most the work (**70%**)
- Analysis and interpretation of data - performed most the work (**70%**)
- Drafting the manuscript - performed most the work (**70%**)

In addition to the work contributed by my supervisor, [Oleksandra Poquet](#) made a substantial contribution (25%) to data acquisition, analysis and interpretation of data, and drafting the manuscript. [Vitomir Kovanović](#), [Nia Dowell](#), and [Caitlin Mills](#) contributed to the work (15% combined) of data acquisition, analysis and interpretation of data, and drafting the manuscript. Professor [Shane Dawson](#), Dr [Christopher Brooks](#), and Professor [Arthur C. Graesser](#) made a substantial contribution (30%) in providing critical revisions to the manuscript.

The work presented in [Section 4.2 \(Chapter 4\)](#) was previously published in International Review of Research in Open and Distance Learning as:

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My contribution was as follows:

- Study conception and design performed most the work (80%)
- Acquisition of data performed most the work (75%)
- Analysis and interpretation of data performed most the work (80%)
- Drafting the manuscript - made a substantial contribution (50%)

In addition to the work contributed by my supervisor, [Oleksandra Skrypnyk](#) made a substantial contribution to data acquisition (20%), analysis and interpretation of data (20%), and drafting the manuscript (50%). [Vitomir Kovanović](#) and Professor [Shane Dawson](#) made a substantial contribution (25%) in providing critical revisions to the manuscript.

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My contribution was as follows:

- Study conception and design performed most the work (75%)
- Acquisition of data performed most the work (75%)
- Analysis and interpretation of data - performed most the work (75%)
- Drafting the manuscript - performed most the work (70%)

In addition to the work contributed by my supervisor, [Oleksandra Skrypnyk](#), [Nia Dowell](#), and [Vitomir Kovanović](#) made a substantial contribution (25% combined) to study conception and design, as well as analysis and interpretation of data. Professor [Shane Dawson](#) and Professor [Arthur C. Graesser](#) made a substantial contribution (30%) in providing critical revisions to the manuscript.

The work presented in [Section 4.4 \(Chapter 4\)](#) was previously published in Proceedings of the Sixth International Conference on Learning Analytics and Knowledge as:

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My contribution was as follows:

- Study conception and design performed most the work (**90%**)
- Acquisition of data performed most the work (**85%**)
- Analysis and interpretation of data - performed most the work (**85%**)
- Drafting the manuscript - performed most the work (**90%**)

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The work presented in [Section 5.2 \(Chapter 5\)](#) was previously published in Proceedings of the Sixth International Conference on Learning Analytics and Knowledge as:

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My contribution was as follows:

- Study conception and design performed most the work (**80%**)
- Acquisition of data performed most the work (**90%**)
- Analysis and interpretation of data - performed most the work (**80%**)
- Drafting the manuscript - performed most the work (**75%**)

In addition to the work contributed by my supervisors, Dr [Jelena Jovanović](#) and [Vitomir Kovanović](#) made a substantial contribution (25% combined) to study conception and design, as well as the analysis and interpretation of data. Dr [Amal Zouaq](#) also contributed to the study conception and design (10%) and providing critical revisions to the manuscript (20%).

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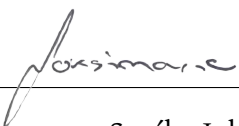
[Joksimović, S.](#), Jovanović, J., Kovanović, V., Gašević, D., Milikić, N., Zouaq, A., and van Saalduinen, J.-P. (2017, under review). Comprehensive analysis of discussion forum

participation: from speech acts to discussion dynamics and course outcomes. Computers in Human Behavior.

My contribution was as follows:

- Study conception and design performed most the work (**90%**)
- Acquisition of data performed most the work (**70%**)
- Analysis and interpretation of data - performed most the work (**90%**)
- Drafting the manuscript - performed most the work (**85%**)

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Srećko Joksimović

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# CHAPTER 1

## Introduction

## 1.1 Preface

The emergence of the contemporary networked society substantially altered the social organization and economic productivity, shaping the flow of capital and changing the types of labour required (Jones, 2015; Castells, 2000; Goodyear, 2014). Changes in the skills and knowledge necessary for successful life and work in an increasingly complex and digitally connected world, further influenced educational systems (Goodyear and Carvalho, 2014b; Jones, 2015; Siemens, 2008). The main premise of this transition was that learning should be taken outside the traditional classroom – i.e., institutional boundaries – becoming global in nature and delivered through digital technologies (Harasim, 2000; Garrison, 2011; Goodyear and Carvalho, 2014b). Network society also brought an abundance of information available, whereas emerging models of communication reshaped practice and pedagogy of online education, bringing research on *learning networks* into the mainstream of educational and social science research (Harasim, 2000; Garrison, 2011; Castells, 2004; Siemens, 2008; Goodyear and Carvalho, 2014b).

The main focus of the contemporary research on learning networks stems from the premise that “learning cannot be designed directly and it can only be designed *for*” (Jones, 2015, p.12). As such, the existing literature is primarily oriented towards retrospective analysis of learning networks and informing design of future tasks and recommendations for learning (Goodyear and Carvalho, 2014a). Research on learning networks mainly focuses on evaluation of educational methods, investigation of learners’ perceived experiences of networked learning, or analysis of online discussion transcripts using mainly qualitative research methods (Goodyear and Carvalho, 2014b; Jones, 2015). Although providing invaluable insights for understanding learning in networked settings, the nature of commonly applied approaches does not necessarily allow for providing means for understanding learning as it unfolds. In that sense, I rely on the interdisciplinary field of learning analytics to develop methods that would enable *assessment for learning* in the scope of learning networks, and thus, enabling learners and teachers to make informed decisions about the learning process as it unfolds.

Learning analytics, therefore, presents a complementary research strand to the contemporary research on learning networks. For example, utilizing methods of social network analysis as a commonly applied approach in learning analytics research (Dawson *et al.*, 2014), researchers tend to examine interactions occurring in learning networks, emerging roles learners obtain in the learning process or understand the importance of social positioning for predicting learning outcome (Dowell *et al.*, 2015; Gaevi *et al.*, 2013). Methods of automated content analysis are frequently applied to obtain timely and comprehensive insights into the topics being discussed in networks of learners or providing understanding of knowledge building processes that unfold in learning networks (Whitelock *et al.*, 2014; Kovanović *et al.*, 2016). However, existing research in learning analytics does not provide a consolidated and theory informed model for studying learning networks that would identify dimensions necessary for informing research and practice.

Of particular interest for my research are learning networks emerging from learning with Mas-

sive Open Online Courses (MOOCs). MOOCs emerged as one of the promising approaches to facilitating learning in networked settings and shifting education towards more open and lifelong learning (Siemens, 2008; Daniel, 2012). Although research on learning with MOOCs have attracted significant attention, several authors voiced their concerns on insufficient theoretical grounding found in existing studies (DeBoer *et al.*, 2014; Reich, 2015). Regardless of a vast amount of data available on students activity in different learning platforms, there is still very little on what aspects actually contribute to learning in MOOCs (DeBoer *et al.*, 2014; Reich, 2015). On the other hand, while it is important to rely on commonly used educational metrics to allow for generalizability across different settings, a holistic approach is needed to understand and interpret observed learning-related constructs and their association with learning, taking into account specific educational contexts (DeBoer *et al.*, 2014; Evans *et al.*, 2016; Vu *et al.*, 2015). Thus, one of the nuances of contemporary MOOC research also stems from the understanding that learning at scale differs from that in more traditional forms of education in many aspects, such as, the magnitude and format of data about students learning, diversity of students background, intents, or socioeconomic status (Reich *et al.*, 2016).

My thesis aims at broadening the existing body of research on learning networks emerging from learning with MOOCs. As such, my research focuses on developing a conceptual analytics-based model for the study of learning networks. The model offers a definition of constructs necessary for comprehensive understanding of learning in networked settings, along with their mutual relations. Utilizing advanced, theory-driven learning analytics methods, my research provides operationalizations of the proposed constructs as means for implementation of assessment for learning and advancing teaching and learning in learning networks. Finally, my thesis offers an empirical evaluation of the proposed model across a wide range of learning scenarios emerging from learning networks formed in MOOCs.

## 1.2 Research goals and questions

My research centers around three overarching goals. The first goal of my thesis assumes development of the conceptual analytics-based model for studying learning networks in the context of learning with MOOCs and providing means for the comprehensive understanding of learning in this particular setting. In so doing, I defined my first research question as follows:

**Research Question 1:** *What are the fundamental, theoretically sound, dimensions of learning networks that are necessary for providing comprehensive assessment for learning in MOOCs at the individual and network level? How can we conceptualize mutual relationships between these constructs?*

The second goal of my thesis centers around providing means for the implementation of assessment for learning that occurs in learning networks emerging from learning in MOOCs. Specifically, here I provide operationalization for the measurement of the constructs introduced within the proposed conceptual model, as well as outline the environments and tasks necessary to elicit identified measurements. Identifying such measurements represents an essential step towards scaling up the

analytics-based approaches for studying learning networks into the context of MOOCs. This goal has therefore been defined as:

**Research Question 2:** *How can the fundamental dimensions of learning networks, as identified in the first research question, be operationalized in the context of learning with MOOCs?*

The third goal of the present thesis focuses on the empirical validation of the proposed conceptual analytics-based model across various learning settings. These learning environments range from highly distributed settings that employ various social media to support interactions in learning networks, to more structured environments where interactions occur within a single learning platform. Implementation of the empirical instances of the proposed analytic-based model should provide a sound basis for understanding factors that promote learning in learning networks emerging from interactions in MOOCs. However, given the most commonly employed approaches to studying learning networks (Jones and Steeples, 2002; Jones, 2015), I defined two broad groups of questions. Specifically, the first group of questions focuses mainly on investigating structure of learners' interactions, whereas the second perspective centers around analyzing learner generated content during the knowledge building process.

The group of questions that focuses on structural properties of learning networks, aims at examining how learning networks evolve and how different network formation help us providing comprehensive understanding of outcomes of learning. In so doing, each of the studies tends to complement investigation of the network structure with the analysis of learner generated discourse to provide salient explanation of the association between structure and discourse. Thus, two subquestions that implement proposed conceptual analytics-based model primarily from the *network-based* perspective are defined as follows:

**Research Question 3.1:** *What are the factors that drive the formation and structure of learning networks emerging in the context of learning with MOOCs?*

**Research Question 3.2:** *How does the formation and structure of learning networks affect the association between learner engagement and learning outcome in the context of learning with MOOCs?*

On the other hand, the goal of the analysis rooted in the *discourse-based* perspective of the implementation of the proposed conceptual analytics-based model is on providing extensive understanding of the processes of knowledge building and sharing in learning networks emerging from learning in MOOCs. Moreover, the this line of studies also investigates to what extent and how the processes of knowledge building and shared meaning frame structures of learning networks and define underlying processes that drive network formation. Therefore, the two research questions that primarily employ discourse-based perspective in studying learning networks are defined as follows:

**Research Question 4.1:** *What processes of knowledge construction in learning networks can be extracted with automated learning analytics methods?*

**Research Question 4.2:** *How does collaborative knowledge construction and shared meaning shapes learning networks?*

### 1.3 Methodology

Given that the main focus of the thesis is on the development of the conceptual analytics-based model that would allow for the assessment for learning in learning networks emerging from learning with MOOCs, in answering my **first research question**, I structured my research around the evidence-centered design (ECD) framework (Section 2.2). The ECD framework consists of five parts: (1) domain analysis, (2) domain modeling, (3) conceptual assessment framework, (4) assessment implementation, and (5) assessment delivery (Mislevy *et al.*, 2003). My focus here is on the conceptual assessment framework (CAF), which allows for dividing the assessment design into its functional components (Mislevy *et al.*, 2003). Central to CAF are the student model (defines a set of attributes to be assessed), the evidence model (defines a set of rules about the observations that constitute evidence about the student model attributes), and the task model (provides a framework for obtaining the evidence needed for the evidence model). Throughout my thesis, I observe *student model* in the broadest context as defining a set of attributes that should be assessed in order to understand learning networks (Section 2.2). The design of the *student model*, or conceptual analytics-based model as defined in this thesis, has been informed by the existing research in networked learning, learning analytics, and learning sciences.

The main focus of the **second research question** is on providing an operationalization of the constructs introduced within the proposed model for studying learning networks emerging from MOOCs. Network learning research recognizes various approaches (e.g., content analysis, focus groups) and relies on a wide spectrum of learning theories (e.g., actor-network theory, connectivism) in studying learning networks (Goodyear and Carvalho, 2014a; Jones, 2015; Jones and Steeples, 2002). Nevertheless, this thesis aims at operationalizing the model of studying learning networks in a way that would allow for understanding factors that drive learning in the context of MOOCs, without necessarily relying on principles of a particular learning theory. Moreover, the notion of *design for learning* (Jones, 2015; Goodyear and Carvalho, 2014b) assumes that the focus of the analysis of learning networks is always “activity-centered” (Goodyear and Carvalho, 2014b, p.18). However, “activity cannot be designed: it is emergent” (Goodyear and Carvalho, 2014b, p.18). Therefore, in operationalizing focal dimensions necessary for understanding learning networks and providing means for assessment for learning, it seems reasonable to focus on the concept of *engagement*, as an overarching construct in the field of education, that brings together “many separate lines of research under one conceptual model” (Apleton *et al.*, 2006, p.427). Engagement, in this context, is also emergent and cannot be designed. We are able to design environments and activities to foster learners engagement. Finally, engagement is also viewed as a product of learners’ activity in the context of learning networks. Therefore, in operationalizing fundamental constructs of the proposed conceptual analytics-based model for studying learning networks, I further rely on the re-conceptualization and re-definition of the existing engage-

ment framework, contextualizing this particular learning-related construct (i.e., engagement) for purposes of understanding learning with MOOCs (Section 3.2).

With respect to studying learning networks emerging from learners' interactions in MOOCs and informing teaching and learning with MOOCs (RQ3.1-RQ4.2), my research builds on the foundational principles of learning analytics to provide means for the implementation of the assessment for learning (Gašević *et al.*, 2017). Incorporating, thus, learning analytics as a constituent of the pedagogy (Knight *et al.*, 2013), I developed various analytics-based models for understanding complex knowledge building skills and measuring sophisticated dimensions of learning. In so doing, I built on the consolidated model of learning analytics that identifies three main characteristics of the field – theory, data science, and design (Gašević *et al.*, 2017). Theory has been recognized as a critical aspect of learning analytics research in informing questions asked, methods used for designing studies and analyzing data, as well as interpreting results and informing existing theory and practice (Reimann, 2016; Wise and Shaffer, 2015; Gašević *et al.*, 2017). Data science methods and techniques are essential to the field of learning analytics as being enablers of the four phases established in the definition of learning analytics (Long *et al.*, 2011) - i.e., collection, measurement, analysis, and reporting (Gašević *et al.*, 2017). Finally, design relates to the (i) provision of opportunities for learning analytics users to gain insights into learning through interaction and visualization design, (ii) conducting research based on rigorous principles through study design, and (iii) promotion of the effective learning experience through the study design (Gašević *et al.*, 2017).

From the *theoretical perspective*, my research is primarily based in findings and conceptualizations of the existing network learning research (Jones and Steeples, 2002; Jones, 2015). Goodyear and Carvalho (2014a) posit that *learning networks* should represent a main focus of inquiry in the learning sciences in general, and networked learning research in particular. Moreover, the principle of *indirect design* - i.e., design for learning, instead of designing learning - that is recognized in networked learning research (Jones, 2015; Goodyear and Carvalho, 2014a), also aligns with the pedagogical and epistemological assumptions adopted in my research. Therefore, networked learning, as the educational paradigm for the age of digital networks (Jones, 2015), provides an appropriate context for defining the properties of learning networks that should be observed in order to obtain a comprehensive portrait of learning with MOOCs.

Each of the empirical studies presented in my thesis is *designed* in accordance with the pragmatic research paradigm, relying on the mixed methods approach (Johnson and Onwuegbuzie, 2004). Although with the main focus on the quantitative methods, my research also employs qualitative research techniques to explore “social and psychological world” (Johnson and Onwuegbuzie, 2004, p.18) relating on characteristics of language and discourse employed in social interaction (Section 4.3 or Section 5.2) or contextual factors that frame communication in learning networks (Section 4.4 or Section 5.3). Pragmatism, focuses on action, trying to complement techniques of quantitative and qualitative research in order to provide answers to complex problems. Specifically, pragmatic principles



built on the assumptions that solving a problem should consider both empirical and practical consequences (Johnson and Onwuegbuzie, 2004). This further aligns with the main tasks of learning analytics, as being recognized in developing measures that “can (a) offer practical insights into learning processes and outcomes, and (b) be theoretically interpreted” (Gašević *et al.*, 2017, p.65). Finally, in addition to the general stance of applying a pragmatic approach, each of the inquiries was framed around the existing learning theories, aiming at investigating principles of connectivism (Section 4.2 and Section 5.2), development of social capital (Section 4.3), or investigating the importance of social ties based on the assumptions of Simmel’s theory of social interaction (Simmel, 1950), to name a few.

Aiming at developing conceptual analytics-based model that would allow for applications of learning analytics methods and approaches for the study of learning networks emerging from learning with MOOCs, my research heavily draws on methods, techniques, and algorithms of *data science*. As the most commonly applied method for studying social interactions, the empirical research introduced in my thesis often utilizes methods of descriptive and statistical social network analysis Chapter 4. However, trying to provide more comprehensive insights into the learning processes occurring in learning networks and the quality of discourse and emerging interactions, I also leverage methods and techniques of machine learning, natural language processing, and statistical network analysis, as well as rely on the computational linguistic methods Chapter 5.

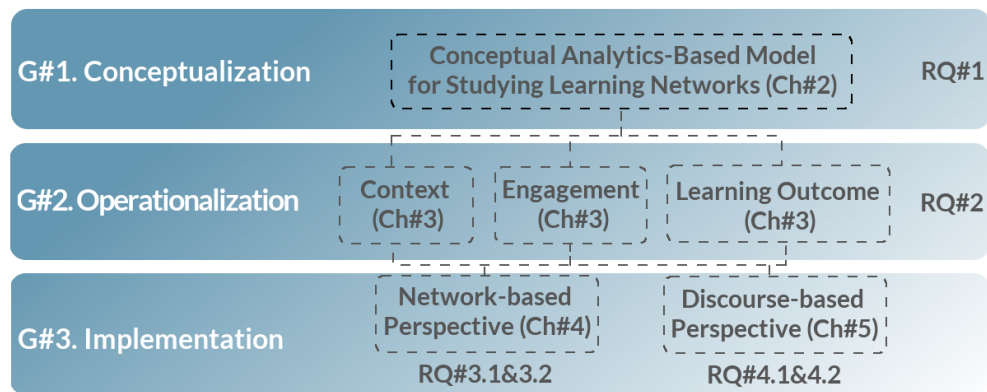
## 1.4 Thesis in brief

Figure 1.1 outlines the structure of the thesis across the three main goals identified in the present research. Each of the chapters included in the thesis addresses one or more research questions, incorporating one or more peer-reviewed publications that constitute the core of the particular chapter. For each of the chapters I also provide introduction and summary as an outline of how each of the chapters and accompanying publications comprise a holistic line of research aimed at advancing understanding of learning networks emerging from learning with MOOCs.

In the remaining of this section, I provide a brief overview of each chapter included in the thesis and how they contribute to the identified research goals.

### 1.4.1 Overview of chapter two - Model Definition (RQ1)

Chapter 2 introduces the conceptual analytics-based model for understanding learning networks that I propose in this thesis. The main focus of the chapter is on defining constructs of the conceptual model that would allow for understanding learning networks as well as outlining the relationships between the identified constructs, thus providing means for implementation of assessment for learning in networked settings. The model introduced in Chapter 2 heavily draws on the ECD model of educational assessment, and particularly conceptual assessment framework (CAF), in defining fundamental dimensions of learning networks that should be observed in understanding learning at individual and network level. As such, this chapter provides foundation for the remaining research conducted within



**Figure 1.1.** Overview of the thesis structure across the three main goals identified in the present research.

this thesis.

**Research contributions:**

- The chapter introduces a conceptual analytics-based model for studying learning networks and providing means of assessment for learning with MOOCs.
- The proposed model outlines the definitions of the learning-related constructs that form the model, along with their mutual relationships, necessary for comprehensive exploration of learning networks.
- The proposed model provides a conceptual framework for designing, implementing, and customizing the analytics for learning and understanding learning networks emerging from learning with MOOCs.

**Research output:**

1. Joksimović *et al.* (2017). “Studying Learning in Non-formal Digital Educational Settings” - An article introducing the conceptual model for studying learning networks and assessment for learning in the context of non-formal digital educational settings, such as with MOOCs, published by the SRI International as a part of Analytics4Learning report series.

#### 1.4.2 Overview of chapter three - Model Operationalization (RQ2)

Chapter 3 builds on the work introduced in the previous chapter by providing operationalization for the constructs that comprise the proposed conceptual analytics-based model for studying learning networks. Specifically, Chapter 2 provides definition of the dimensions of learning networks, recognized within the proposed model and theorizes relationship between those constructs. Observed through the ECD model and conceptual assessment framework, Chapter 2 defines the elements of the *student model* and only briefly introduces *evidence* and *task models*. Chapter 3, therefore, provides more thorough, theory driven, operationalization of these two models, proposing also the approaches to measuring the constructs of learning networks in the context of MOOCs.

In so doing, the study introduced in [Chapter 3](#), presents a systematic literature review of approaches to model learning in MOOCs offering an analysis of learning related constructs used in the prediction and measurement of learner engagement and learning outcome. Based on the literature review, I identify current gaps in the research, including a lack of solid frameworks to explain learning in open online setting. Finally, the study puts forward a novel framework suitable for studying learning networks based on a well-established model of learner engagement ([Reschly and Christenson, 2012](#)). The framework is intended to guide future work studying the association between contextual factors (i.e., demographic, classroom, and individual needs), learner engagement (i.e., academic, behavioral, cognitive, and affective engagement metrics) and learning outcomes (i.e., academic, social, and affective). As such, the proposed framework provides operationalization for the constructs of the conceptual analytics-based model for studying learning networks introduced in [Chapter 2](#) and affords further implementation of assessment for learning in MOOCs.

#### **Research contributions:**

- The chapter provides an operationalization of the constructs introduced within the conceptual analytics-based model for studying learning networks in the context of MOOCs.
- In so doing, I conduct a systematic literature review of the existing body of research in MOOCs that tries to model learning in this particular setting.
- The second part of the contribution is framed around the redefinition of the existing educational framework in order to account for specific aspects of learning in MOOCs. Specifically, following [Reschly and Christenson \(2012\)](#) research, I propose a model for studying the association between context, learner engagement and learning outcome.
- Having a generally accepted conceptualization of engagement, as proposed in this chapter, should allow for explaining factors that influence learning with MOOCs. Moreover, the proposed conceptualization of engagement should also allow for generalization of factors that influence learning in networked settings, allowing for comparison across different platforms or with diverse context (such as traditional online or face to face learning).
- Such a conceptualization should also allow for moving beyond observing learner “click data” and exploring how quantity and quality of interactions in learning networks could predict course outcome and persistence, thus providing more salient connection with existing learning theories and practices, allowing for the implementation of assessment for learning.

#### **Research output:**

1. [Joksimović et al. \(2017\)](#). “How do we Model Learning at Scale? A Systematic Review of the Literature” - A journal article that presents a systematic review of the literature that focuses on modeling learning in MOOCs. Building on the findings from the reviewed literature, the article further proposes redefinition and re-operationalization of the model that of the association between context, engagement, and learning outcome, originally developed in the context of for-

mal learning by [Reschly and Christenson \(2012\)](#). The study has been submitted to the Review of Educational Research journal, and currently the second round of review is in progress.

#### 1.4.3 Overview of chapter four - Network-based perspective to studying learning networks (RQ3.1 & RQ3.2)

To evaluate the proposed analytics-based conceptual model, I conducted several empirical studies that introduce novel analytics methods for the study of learning networks and for assessing and understanding learning (and teaching) in MOOCs. Utilizing various advanced statistical methods and building on the approaches for social network and discourse analysis, my research aimed at providing basis for identifying learning-related constructs that would explain the importance of structure of learner interactions, discourse, and temporal aspects of learning networks. In so doing, each of the empirical studies introduced in this and the following chapter observes more than one form of learner engagement (as introduced in [Chapter 3](#)) in various contexts, explaining either academic or social outcomes of learning in networked settings ([Figure 1.1](#)).

The first of the two chapters that provide implementation of the proposed conceptual analytics-based model for studying learning networks, focuses primarily on studying formation and structure of networks emerging in the context of MOOCs. This chapter, introduces studies that primarily utilize social and socio-technical interaction-based perspective in studying learning networks. Contemporary learning theories and approaches (e.g., distributed cognition, communities of practice or connectivism) posit that learning is no longer (as argued in traditional theories of learning) an isolated individual process ([Siemens, 2008](#); [Siemens et al., 2015](#); [Eynon et al., 2016](#)). With the technological advancements in recent years, learning occurs in networks through interactions with our peers and resources, relying on available technological affordances ([Siemens, 2008](#); [Eynon et al., 2016](#)). In such conceptualization, it seems crucial to understand emerging roles learners and teachers attain in these interactions and who tends to learn with whom in distributed settings ([Siemens et al., 2015](#); [Eynon et al., 2016](#)). Moreover, to support teaching and improve learning, it is also important to provide for more valid inferences and identify the determinants that would enable contextually salient understanding of learning in networked settings ([Garrison, 2011](#); [Moore, 1993](#)).

##### **Research contributions:**

- I provide insights into the emerging roles of social and technical actors in learning networks through the process of knowledge building and sharing
- The analysis indicate that over the course progression, a group of nodes developed network positions comparable to those of facilitators
- The findings further suggest that learners in the context of learning networks, emerging from various social media (such as Twitter, blogs, or Facebook), tend to connect around thematic markers of common interest
- I further examine the importance of learners' social identity, as being depicted through learner

generated discourse, for the development of social capital in learning networks

- The findings detail the role of language and media affordances as means to reveal important aspects of learners' activity in learning networks
- In order to provide more valid inferences and identify determinants that provide contextually salient understanding of learning networks, I account for social dynamical processes that frame learners' interactions in the context of learning at scale.
- utilizing methods of statistical network analysis, results show that the tendency to link with peers with similar social identity, as well as endogenous network effects such as popularity or reciprocity, had significant implications for understanding the importance of learner social positioning within the network of learners.

#### **Research output:**

1. [Skrypnyk et al. \(2015\)](#). "Roles of course facilitators, learners, and technology in the flow of information of a CMOOC" - A journal article that focuses primarily on the structural and temporal dimensions of learners' interactions, in order to analyze learning networks emerging from social and socio-technical interactions within various social media (i.e., Twitter, Facebook, and blogs) used in a connectivist MOOC. The article was published in the International Review of Research in Open and Distance Learning journal.
2. [Joksimović et al. \(2016\)](#). "Exploring Development of Social Capital in a cMOOC Through Language and Discourse" - A journal article that extended the approach applied by [Skrypnyk et al. \(2015\)](#), to account for discourse properties in analyzing learning networks within a connectivist MOOC context. The article has been submitted to the Internet and Higher Education journal, and currently the second round of review is in progress.
3. [Joksimović et al. \(2016\)](#). "Translating Network Position into Performance: Importance of Centrality in Different Network Configurations" - A full conference paper that focuses on examining to what extent structure of learning networks provide basis for understanding the importance of various forms of engagement. The paper was presented at the Sixth International Conference on Learning Analytics and Knowledge (LAK'16) and was nominated for the best paper award.

#### **1.4.4 Overview of chapter five - Discourse-based perspective to studying learning networks (RQ4.1 & RQ4.2)**

As a complementary approach to the methods introduced in [Chapter 4](#), this chapter focuses primarily on examining discourse as means for explaining emerging social structures and for providing a basis for developing "interpretative models" ([Eynon et al., 2016](#), p.8) that could potentially provide more comprehensive insight in learning processes. The sections in this chapter, thus, took a somewhat different stance from the publications introduced in the previous chapter, focusing on the analysis of discourse and how temporal changes of discourse help understanding learning networks. Moreover, the chapter also highlights the importance of accounting for the structure of social interaction

and shows to what extent actions reflected through language and discourse help explaining emerging network structures, as well as, how eventual association between discourse and structure helps better understanding of factors that are potentially associated with learning outcomes.

**Research contributions:**

- I propose a novel analytics approach that integrates tools and techniques for automated content analysis and social network analysis.
- I propose a graph based approach to extracting most prominent topics emerging from discussions within learning networks emerging from social media.
- I propose an automated approach to the identification of common groups of speech acts emerging from discussion forums in the context of MOOCs.
- The findings show that learners in distributed networked settings were primarily focused on the course topics they were interested in, regardless of the topics suggested by the course facilitators, while the technology had a significant impact on how learners discussed certain topics.
- The findings also revealed how different conversational patterns evident in learners' contributions on discussion forums revealed rather distinct social dynamics that framed the formation of learning networks.
- Finally, through the combination of discourse analysis with the methods of statistical social network analysis, I was able to interpret the association of both social network centrality and forum participation with the final course grades in learning networks formed in MOOCs.

**Research output:**

1. [Joksimović et al. \(2015\)](#). "What do cMOOC participants talk about in social media?: a topic analysis of discourse in a cMOOC" – A full conference paper that focuses on studying the process of knowledge sharing and collaborative learning opportunities in online settings. The article was presented at the Fifth International Conference on Learning Analytics and Knowledge (LAK'15).
2. [Joksimović et al. \(2017\)](#). "Comprehensive analysis of discussion forum participation: from speech acts to discussion dynamics and course outcomes" – A journal paper that focuses to the development of a comprehensive analytics-based approach that would allow for understanding various dimensions of learner generated discourse and the structure of the underlying social interactions. The manuscript has been submitted for review to the Computers in Human Behavior journal.

#### **1.4.5 Overview of chapter six - Summary and moving forward**

The final chapter in the thesis provides a summary of contributions of my research and outlines several promising directions for future research.

## Model Definition – Learning Analytics and Assessment for Learning

## 2.1 Preface

This chapter focuses on addressing the first research question and providing means for fulfilling the first goal of the present thesis (Section 1.2). Proposing a conceptual analytics-based model for studying learning networks, the chapter establishes the foundation for the research presented in the remainder of the thesis. As such, this chapter is structured around a publication that outlines fundamental dimensions of learning networks (Section 2.2), necessary for providing comprehensive insights into the factors that contribute to understanding learning in networked settings in general, and learning networks emerging in the context of learning with MOOCs, in particular. Being rooted in the networked learning literature – primarily in the work of Goodyear (2002, 2004), Goodyear and Carvalho (2014b) and Jones (2008) – and the assumption that “networked learning is inherently social” (Goodyear, 2002, p.51), the proposed conceptual model contributes to the development of the next generation of research that studies learning networks emerging from learning at scale (Reich, 2015).

Before elaborating further on the proposed conceptual model and positioning it within the current literature (Section 2.2), I will provide a broader background and introduce the main concepts that framed the research presented in this thesis. Thus, over the next several sections I talk about learning and engagement (Section 2.1.1), explaining how these two concepts were operationalized through my research. I briefly introduce the concept of networks (Section 2.1.2) and particularly learning networks, as the main focus of my research (Section 2.1.3). Moreover, I introduce the notion of assessment for learning and explain how my research is structured around this particular concept. Finally, at the end of the chapter, I reflect on the proposed model and outline its connection with the remaining chapters in the thesis (Section 2.3.1).

### 2.1.1 Learning & Engagement

The term learning has been used very broadly, with different meanings in various contexts (Illeris, 2004, 2007; Kolb, 1984; Fenwick *et al.*, 2015). Many theoretical shifts occurred over the years as approaches to interpreting what accounts for learning and reflecting some of the prevailing perspectives affecting learning research at the time. Thus, behavioral, cognitivist, socio-cultural, linguistic or semiotic, neuroscience, and socio-material (or socio-technical) paradigm shifts were commonly recognized in the educational literature (Goodyear and Carvalho, 2014b). Although a deep analysis of each of the theoretical turns is outside the scope of this thesis, I only want to note that each paradigm represents rather a radical turn in our understanding of learning in a given context (Goodyear and Carvalho, 2014b). In my thesis, I observe learning from a socio-technical perspective that advocates for a constitutive entanglement of social and material in understanding learning in digital environments (Quimno *et al.*, 2013; Bell, 2010).

Within the socio-technical perspective, several major approaches to learning have evolved in the literature, with somewhat different theoretical conceptions of materiality in learning (Bell, 2010; Jones, 2008; Fenwick *et al.*, 2015). The cultural historical activity theory (Igira and Gregory, 2009), actor-



network theory (Latour, 2005), complexity theory (Mason, 2008), and connectivist conceptualization of learning (Siemens, 2005), are perhaps the most prominent arenas among educational researchers (Fenwick et al., 2015; Jones, 2015). Each of the research approaches have similarities “in the ways that they conceptualise knowledge and capacities as being emergent from the webs of interconnections between heterogeneous entities, both human and non-human” (Jones, 2015, p.66). However, there is no single, commonly agreed upon, definition of learning among the socio-technical perspectives and there is even no attempt to synthesize them (Jones, 2015; Fenwick, 2010).

Approaches emerging from the activity theory, such as situated learning or communities of practice, observe learning through certain forms of social co-participation (Lave and Wenger, 1991). Instead of focusing on cognitive processes, the situated learning theory observes social structures and engagement with peers in order to reveal “the proper context for learning to take place” (Lave and Wenger, 1991, p.14). Similar to situated learning, the social practice perspective also builds on the concepts of the activity theory (Jones, 2008), defining practice as a process and activity, highlighting again (perhaps in an indirect way) the importance of learner engagement. Finally, Siemens (2005) argues that knowledge resides in networks and learning is viewed as building connections with peers through constant participation and engagement.

To provide operationalization for the constructs of the conceptual analytics-based model for studying learning networks, I focus on measuring learner *engagement*, as a construct that drives learning and (potentially) predicts learning success (Reschly and Christenson, 2012; Appleton et al., 2006; Trowler, 2010; D’Mello et al., 2017). As such, the concept of learner engagement complements Goodyear and Carvalho (2014a) notion of *activity*, that is being recognized as a main focus in design for learning in networks. Thus, engagement here is also viewed as emergent (i.e., cannot be designed), *encapsulating measurable evidence* of learners activities in learning networks. Moreover, in a certain form, engagement is present in different approaches to the study of learning networks. Given the well-evidenced importance of engagement for learning and learning success (Appleton et al., 2006; Trowler, 2010; Christenson, 2009; Ensminger and Slusarcick, 1992; Christenson et al., 2012), I posit that providing insights into the multidimensional construct of engagement should provide a comprehensive understanding of learning, regardless of the theoretical perspective utilized. I discuss learners’ engagement more thoroughly in Chapter 3, where I am focusing on the operationalization of the constructs of the proposed model for studying learning networks. Relying on the well-established model of the association between context, engagement, and outcome (Reschly and Christenson, 2012), I further provide re-definition and re-operationalization of these three constructs in the context of learning networks emerging from learning with MOOCs (Section 3.2).

### 2.1.2 Networks

In recent years, networks have been studied in wide variety of disciplines, ranging from computer science, communication, sociological and organizational research to health sciences and epidemiology,

to name a few (Castells, 2004; Knappett, 2013; Siemens, 2008; Goodyear and Carvalho, 2014b). Thus, the term has been used very broadly, to describe ecological networks (Sole and Montoya, 2001), epistemic networks (Roth, 2005), or telecommunication networks (Schwartz, 1987), for example. Although with somewhat different perspectives, existing approaches primarily draw on the mathematical studies of networks and graph theory, that define networks as a set of nodes and vertices (i.e., edges) (Freeman, 1978; Barabási and Albert, 1999). Each node and edge, potentially has an attribute (e.g., name or weight), whereas edges between nodes could be directed or undirected (Barabási and Pósfai, 2016; Freeman, 1978; Barabási and Albert, 1999). Certain applications of networks also allow for multiple types of nodes – i.e., multimodal networks (Heath and Sioson, 2009) – and multiple kinds of edges between the nodes – i.e., multiplex networks (Gomez *et al.*, 2013).

Regarding the human organization, networks are not specifically bound to the 21<sup>st</sup> century societies (Castells, 2004). People connected long before the emergence of *network society* (Jones, 2015; Castells, 2004; Knappett, 2013) and “even before they used that term to describe what they were doing” (Goodyear and Carvalho, 2014b, p.9). Initially, those connections were made for exchange of goods, farming, or gathering, for example. Nevertheless, what is different nowadays are the ways we are able to make connections in the digitally connected world. As Castells (2004) argues, the point is not on technology as a factor that determines a society. The point is in the abundance of technological affordances that enabled addressing some of the main shortcomings of the networks – “their inability to manage coordination functions beyond a certain threshold of size, complexity and velocity” (Castells, 2004, p.221).

Of particular interest for my thesis are social and socio-technical networks emerging from learning in digitally mediated settings (Goodyear and Carvalho, 2014b; Siemens, 2008; Haythornthwaite, 2011). The socio-technical perspective (Jarrahi and Sawyer, 2013) affords a strong theoretical rationale for integrating technology into the creation of the structure that effectively enables interactions in computer-mediated settings. Contrary to the mainstream view of the interplay between social and technological dimensions, the socio-technical interaction framework (Creanor and Walker, 2010) treats both aspects as mutually constituted. In our particular context, treating both human participants and technological affordances as being capable of having reciprocal effect prevents the deterministic predictions about how a certain piece of technology provides specific affordances for a set pedagogy. Mutual constitution makes no prior judgment towards the importance of either social or technological aspects and requires analyzing the process of interactions as reciprocal between the contextual interactions and outcomes (Barrett *et al.*, 2006). As further discussed in Chapter 4 and Chapter 5, I employ these two conceptualizations (i.e., social or socio-technical) to examine different factors that contribute to learning - e.g., emerging roles of human and technical nodes (Section 4.2) or importance of social dynamical processes in predicting learning outcome (Section 4.4).

Analyzing networks also implies assuming a certain structure that has to be taken into account. This structure imposes certain relations between humans included in a network or between human

and *materials* (technology) (Knappett, 2013). The term 'network' is thus qualitatively different from a 'community', 'group', or 'family' (Wenger *et al.*, 2011; McConnell, 2006), imposing certain "degree of openness and flux" (Goodyear and Carvalho, 2014b, p.9) that other terms might not capture. Whereas network as a structure does not imply that all peers know each other (communities or groups, for example, do), networking does involve a certain flow or interaction – e.g., flow of information, people, or objects in general (Siemens, 2008). In the context of educational research, networks also have different connotation than communities – e.g., communities of practice (Lave and Wenger, 1991) – being more neutral in terms of having "fewer of these cozy connotations" (Goodyear and Carvalho, 2014b, p.10).

### 2.1.3 Learning Networks & Learning with MOOCs

#### Defining learning networks

The origins of learning networks as a concept can be found in Illich's (1971) thinking on learning webs (Siemens, 2008), few decades before technological affordances allowed for digital networks to fully emerge. Illich (1971) argued that "we can provide the learner with new links to the world instead of continuing to funnel all educational programs through the teacher" (*ibid.*, p.70), thus depending on self-motivated learners, instead of "employing teachers to bribe or compel the student to find the time and the will to learn" (*ibid.*, p.70). However, it took until 1983 before the first learning network actually emerged, aiming at connecting primary and secondary schools using e-mail services (Harasim, 1995, 2000).

The first attempts to define learning networks were made in late 1990s, and were primarily based in understanding networks as physical structures aimed at supporting education. Thus, Harasim (1995) viewed learning networks as "composed of hardware, software, and telecommunication lines" (*ibid.*, p.16) that enable "groups of people" (*ibid.*, p.4) or "communities of learners" (*ibid.*, p.xi) to use computer-mediated communications to "learn together, at the time, place, and pace that best suits them and is appropriate to the task" (*ibid.*, p.4). Likewise, Mayadas (1997) (i.e., US Sloan Foundation), viewed asynchronous learning network as a "network of people – an interactive learning community that is not limited by time, place or the constraints of a classroom" (*ibid.*, p.2). Both definitions, therefore, emphasize "people and learning rather than technology" (Goodyear and Carvalho, 2014b, p.13), focusing particularly on individuals, where technology is primarily understood as means for supporting interactions in networked environments.

The way I frame the association between learning and technology in my thesis is, however, more closely aligned with Bayne's (2015) view of the relationship between individual, education, and technology. Specifically, Bayne (2015) contends that we should observe education and technology as "co-constitutive of each other, entangled in cultural, material, political and economic assemblages of great complexity" (*ibid.*, p.18). Therefore, I conceptualize learning networks as defined by Goodyear and Carvalho (2014b) and as operationalized in the concept of "productive learning networks" (*ibid.*, p.15). It is important to highlight that, opposite to actor-network theory (Latour, 2005), for example, Goodyear

and Carvalho (2014b) do not treat technology as part of social networks. Such understanding provides higher flexibility in framing research around social, technical, or socio-technical factors. An example of such analysis is provided in Chapter 4, where depending on specific research questions, we focus on socio-technical (Section 4.2) or primarily social factors (Section 4.4) to understand learning in formal and informal educational settings.

### Boundaries of learning networks – bringing MOOCs

Although methods and approaches applied in my thesis could be used in broader settings, my research primarily focuses on learning networks emerging from learning with MOOCs. Specifically, I study learning in MOOCs as one of the most prominent ways for implementing and facilitating learning at scale in networked settings. Here, I refer to MOOCs as a planned learning experience within *non-formal, digital* educational settings, used to enable education at scale (Chapter 3). In computer-mediated (networked) settings, as is the context of my research, learning is observed as a dynamic and complex process. Learning, thus, involves student interactions with other students, between students and teachers, and with content (Goodyear, 2002; Halatchliyski et al., 2014). By *non-formal*, I assume any systematic learning activity conducted outside the formal (i.e., institutional, for credit) settings (Eraut, 2000). Finally, *digital (education)*, refers to an emerging approach to learning mediated by various technological methods (Siemens et al., 2015). Digital education brings online, distance and blended learning under a single concept, and could be structured as formal and informal, self-regulated, or lifelong.

The notion of *non-formal, digital educational settings* was introduced with the aim to provide an overarching definition of the context of learning with MOOCs that would capture all the nuances of this particular setting through a more generally accepted categorization of learning environments. Therefore, the paper introduced in the following section (Section 2.2), utilizes this particular definition to outline the conceptual analytics-based model for studying learning networks. Throughout the present thesis concepts of *learning with MOOCs* and *learning in non-formal, digital educational settings*, will be used to describe the primary context of interest for my research.

#### 2.1.4 Assessment for learning

Assessment is essential for measuring student engagement and for understanding learning. As such, assessment is among the most significant elements that shape educational experience (Bennett et al., 2017; Reddan, 2013; Brown and Knight, 1994; Broadfoot and Black, 2004). As Brown and Knight (1994) pointed out, assessment defines “what students regard as important, how they spend their time, and how they come to see themselves as students” (*ibid.*, p.12). Nevertheless, the traditional approaches to assessment have been criticized as not being transformative enough, making “the measurable important instead of making the important measurable” (Trehan and Reynolds, 2002, p.280). Nowadays, as the traditional curricula in higher, adult, and professional education increasingly recognize the im-

portance of developing 21<sup>st</sup> century skills – such as critical thinking, problem solving, information seeking, and digital literacies (Council *et al.*, 2011) – as being critical factors that characterize students who are prepared for increasingly complex life and work environments, there is (perhaps more than ever) a need of rethinking the assessment (Shute *et al.*, 2008; Broadfoot and Black, 2004; Siemens *et al.*, 2015).

Digital technologies and the new approaches to learning and teaching in the digitally connected world, brought a completely new arena for development of more engaging, personalized, and timely assessment (Trehan and Reynolds, 2002). Although initial ideas of self- and peer-assessment date back in 1980s (Boud, 2012; Heron, 1981), recently the necessity of participative approaches to assessment have been even more highlighted, especially in the context of adult and professional online learning (Trehan and Reynolds, 2002; Broadfoot and Black, 2004). However, despite current developments, the assessment in learning networks is still primarily driven with the traditional forms of assessment (Section 3.2). Although existing technology allows for numerous ways for learning to occur, it still limits assessment to quizzes, automatically graded assignments, and multiple choice questions (Trehan and Reynolds, 2002). This further means that most of the assessment in networks is still focused on assessment **of** learning, rather than providing means for assessment **for** learning (Kulkarni *et al.*, 2013).

Learning analytics, however, has a tremendous potential to help addressing some of the identified challenges (Gašević *et al.*, 2015, 2016; Knight *et al.*, 2013). Being utilized either as an assessment **of** learning or as providing means for assessment **for** learning, learning analytics provides tools and methods for assessing complex skills and competencies in a timely and formative manner (Gašević *et al.*, 2016; Knight *et al.*, 2013; Pardo and Siemens, 2014). Specifically, learning analytics methods and approaches have a potential to allow for scaling up methods that can provide, for example, teachers and students with objective measures of learning and that can enable for making informed decisions about assessment. In my research, therefore, I focus on developing methods that would allow for more comprehensive understanding of learning in complex educational settings.

The next section presents a study (Joksimović *et al.*, 2017) that introduces the conceptual analytics-based model for studying learning networks emerging from learning with MOOCs. The model development was structured around the ECD model, and particularly the conceptual assessment framework (CAF), which defines an architecture for the implementation of an assessment delivery systems (Mislevy *et al.*, 2003). The proposed model should allow for obtaining a comprehensive portrait of learning networks emerging from learning with MOOCs at network and individual level (Goodyear and Carvalho, 2014a). Therefore, in defining the key constructs of the proposed model, my research has been primarily rooted in the networked learning research. However, my understanding of the importance of individual agency stems from social learning theories and an assumption that human behavior is guided by constant and “continuous reciprocal interaction between behaviour and its controlling conditions” (Bandura, 1977, p.2). Thus, in defining aspects of the individual agency, I rely on Ban-

dura's (1977; 1986) seminal work and social cognitive theory. As such, the proposed model establishes a framework for the remaining research conducted in my thesis. First, it outlines the potential operationalization for the proposed constructs that is being further discussed in Chapter 3. Moreover, it also outlines the dimensions that are being observed throughout the empirical research presented in Chapter 4 and Chapter 5.

## 2.2 Publication: Studying Learning in Non-formal Digital Educational Settings

The following section includes the verbatim copy of the following publication:

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## Studying Learning in Nonformal Digital Educational Settings

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January 2017

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## Introduction

With the rapid growth of interest in learning analytics, the field continues to mature in all aspects of its analytical methods and techniques, application into practice, and theoretical contributions. As it was initially defined in 2011, learning analytics is “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (Long, Siemens, Conole, & Gašević, 2011, p. 3). The development of learning analytics research was driven primarily by advances in educational technology and the emergence of large-scale data about students’ learning, along with the willingness of educational institutions and corporations to make sense of such data. Learning analytics has emerged as a broad area of inquiry, exploring the multidisciplinary connections that could effectively enhance understanding of individual and collective learning processes (Dawson, Drachsler, & Rose, 2016).

Learning analytics has the potential for studying learning in various educational settings (e.g., online, blended learning) and advancing learning processes (Baker & Inventado, 2014; Gašević, Dawson, Rogers, & Gašević, 2016). Besides traditional online settings or blended learning environments, learning analytics also is applicable in more or less formal educational settings that support learning at scale, such as massive open online courses (MOOCs). MOOCs emerged as a significant trend in changing the landscape of formal, informal, and nonformal learning (Joksimović, Kovanović, Skrypnyk, et al., 2015). Designed as (relatively) short, open (in terms of access) online courses and delivered by various universities, MOOCs could be categorized as a mode of nonformal education, bridging formal and nonformal learning in networked environments. Thus bringing promise of shifting educational paradigms and expanding access to learning for everyone, MOOCs also introduced a challenge to applying learning analytics in researching learning in networks.

Although research in learning analytics in general and learning analytics for MOOCs in particular have attracted significant attention, most of the current studies on learning in traditional online and non-formal educational settings has failed to account for learning theories (Gašević et al., 2016; Wise & Shaffer, 2015). Various researchers have criticized MOOC research for being primarily observational and failing to provide a causal relationship between observed metrics of student engagement in networked settings and learning (Reich, 2015). Regardless of a vast amount of data available on students’ activity in different MOOC platforms, there is still a very little or no evidence on what aspects actually contribute to learning in MOOCs (DeBoer, Ho, Stump, & Breslow, 2014; Reich, 2015). One of the nuances of contemporary MOOC research also stems from the understanding that learning in nonformal educational settings differs from that in more traditional forms of education in many aspects (e.g., the magnitude and format of data about students’ learning, diversity of students’ background, intents, or socioeconomic status) (DeBoer et

al., 2014; Evans, Baker, & Dee, 2016; Glass, Shiokawa-Baklan, & Saltarelli, 2016; Reich, Stewart, Mavon, & Tingley, 2016).

The main goal of this research was therefore to advance learning analytics methods for assessing learning quality in non-formal digital educational environments. Specifically, we propose a conceptual analytical model for assessing learning in networked settings that offers a definition of the model constructs along with their mutual relations, operationalisations for the measurement of those constructs, and automated methods that can scale up the applicability of the proposed model.

## Theoretical Framework

In the development of the conceptual model for understanding and assessing learning in diverse and complex nonformal digital educational settings, we drew on the evidence-centered design (ECD) framework (see Figure 1) (Mislevy, Almond, & Lukas, 2003). ECD is a modular process that allows for building complex measurement models, scaffolding assessment designers in modeling learning goals and articulating assessment decisions (Mislevy et al., 2003). The ECD framework is built on previous work on evidentiary reasoning in assessment (Mislevy, 1994), graphical probability models (Almond, 1995), and intelligent tutoring systems (Steinberg & Gitomer, 1996). The ECD framework consists of five parts: (1) domain analysis, (2) domain modeling, (3) conceptual assessment framework, (4) assessment implementation, and (5) assessment delivery (Mislevy et al., 2003). Our focus here is on the conceptual assessment framework (CAF), which allows for dividing assessment design into its functional components. Central to CAF are the student model (defines a set of attributes to be assessed), the evidence model (defines a set of rules about the observations that constitute evidence about the student model attributes), and the task model (provides a framework for obtaining the evidence needed for the evidence model). Thus, our research is centered around the following objectives:

1. **development of an analytical model of learning in networks** that offers a definition of the model's constructs along with their mutual relations (i.e., **student model**),
2. empirical validation of the conceptual analytical model (i.e., task model),
3. *operationalization for measurement* of those constructs (i.e., evidence model), and
4. **development of automated methods** to scale up the applicability of the proposed conceptual analytical model.

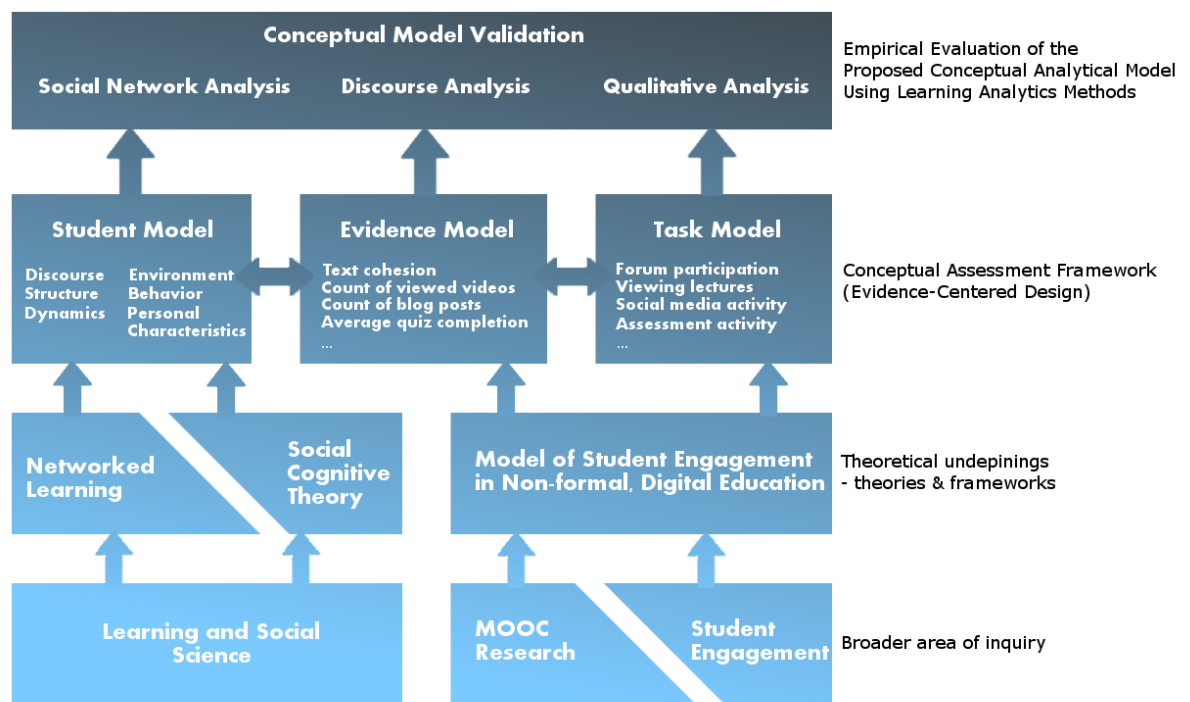
In order to achieve the objectives of our research, we defined the following research questions:

1. How can learning analytics methods be used to construct a comprehensive model for understanding learning in nonformal educational settings?

2. How can this new model be operationalized? Specifically, how are the constructs of the model and their mutual relationships defined?
3. What variables should be used in such a model? That is, how can we measure the proposed constructs, and how are these variables conceptualized in the context of learning in nonformal settings?
4. To what extent can such a model enable for the development of automated methods for assessing learning in nonformal settings?

Answering the research questions will result in several contributions to the body of knowledge in learning analytics. First and foremost, we offer a comprehensive - and possibly the first - conceptual (analytical) model that allows for studying learning and knowledge in non-formal digital educational settings. Further, this research will provide an extensive set of variables to measure proposed constructs so as to enable instructors to design appropriate learning interventions. Finally, we will propose methods for automated extractions of the variables that comprise the developed model.

**Figure 1: Overview of the theoretical approaches applied in modelling conceptual analytical framework**



# Student Model - A Conceptual Model for Understanding Learning at Scale

## Theoretical Underpinnings

Arguing for the importance of conceptualizing learning analytics research on the basis of existing learning theories, Gašević et al. (2016) claimed that “a theoretically driven approach leads to an ontologically deep engagement with intentions and causes, and the validation of models of learning, learning contexts, and learner behavior” (p.70). Thus, the proposed conceptual analytical model for studying learning in non-formal digital settings builds on networked learning research to inform development of the constructs for the proposed model, as well as their mutual relationships. Specifically, the proposed student model takes the form of a conceptual analytical model that relies on learning analytics methods and techniques to provide a comprehensive understanding of learning in non-formal digital education. The constructs of the proposed model and their mutual relationships are formulated based on the existing research in networked learning and validated through a series of empirical studies.

This research focuses on networked learning in technology-mediated environments. Networked learning, an emerging paradigm in the learning and social sciences with theoretical, pedagogical, and practical importance (Dirckinck-Holmfeld, Hodgson, & McConnell, 2012), is defined as a learning approach that relies on information and communication technologies to support connections among learners, between learners and teachers, and between learners and learning resources (Goodyear, 2002, 2004). The use of technology affects every aspect of learning and mediates connections within a learning community. Therefore, the main goal of networked learning research is to understand how various technological affordances can influence pedagogy and learning design to foster deep and meaningful learning (Dirckinck-Holmfeld et al., 2012; Steeples & Jones, 2002). In recent years, networked learning research takes a broader critical approach in studying collaborative and cooperative learning in formal and informal learning settings. According to such new perspectives, the central topics of networked learning research are connections and human-human interaction that occur in a networked learning community (Goodyear, 2004; Dirckinck-Holmfeld et al., 2012). With the technological advances and development of education technology, various theories and methods have emerged with aims of advancing research of networked learning (Gee, 2004; Wenger, 1998).

The proposed analytical model is primarily rooted in the work of Goodyear (2002) and Jones (2008) and the assumption that “networked learning is inherently social” (Goodyear, 2002, p. 51). Moreover, it relies on the premises of social cognitive theory and Bandura’s work (Bandura, 1977, 1986). The model constructs are grouped within two broad categories. In the central part are elements related to collaborative and cooperative learning in networked settings. Specifically, these are the determinants of

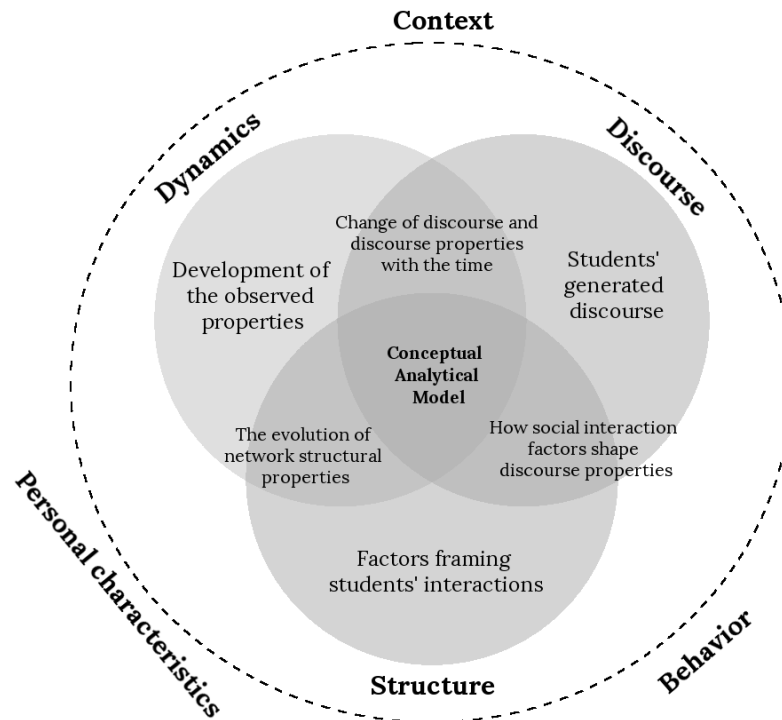
learning in non-formal settings that emerge from students' interaction with their peers, media, and/or learning resources within a given platform. The second category of model properties focuses on a student's individual agency. Context, personal student characteristics, and student behavior provide a framework for more salient inferences about the learning processes in the observed environment.

## Networked Learning Analytics Demystified

The three central elements of the proposed analytical model are *structure*, *discourse*, and *dynamics* (Figure 2). The proposed elements are interdependent in the sense that the model also observes how social interaction factors shape discourse properties, as well as how temporal dynamics frame network structural properties and influence development of discourse. The **structure** of students' social interactions explains the regularities in communication between peers and instructors, revealing main (social and technical) factors that frame this interaction and influence learning processes. Student-generated **discourse** provides further insight into the quality of learning. Relying mainly on linguistic indicators of text cohesion and coherence, the construct explains the level of students' cognitive and affective engagement, as well as a comprehension of learning materials. **Dynamics** examines the importance of the temporal dimension for the association between students' activity and learning. It also accounts for the development of behavioral variables. The three constructs of structure, discourse, and dynamics have been empirically validated in our research that is presented here.

The proposed framework also accounts for **contextual**, **behavioral**, and **personal characteristics** to i) comprehensively describe the learning environment, learning context, and learners, and ii) enable for a holistic interpretation of the model constructs and their relationships. Thus, the **contextual analysis** accounts for the factors that define the specific learning context and the nature of interaction between two or more individuals in a social network that is derived from the collective behavior. **Personal characteristics** include students' demographic data, motivational factors, and previous experience, among others. **Behavioral variables** describe aspects of the academic, affective, and cognitive students' engagement within a given course. Further sections provide an operationalization of the variables used to explain those three characteristics, along with the proposed methods for the automated extraction of the metrics used to measure each of them.

**Figure 2: Elements of the proposed student model for studying learning in non-formal, digital educational settings**



### Structure

Studying the structure of interactions in networked learning settings is essential for understanding processes that drive learning in non-formal education. The importance of interactions among students, between students and teachers, and between students and resources has been highlighted in the definition of networked learning provided by Steeples and Jones (2002). Steeples and Jones further posited that the definition implies the social nature of learning, where knowledge is socially constructed and represents a potential outcome of the use of networks. It should be noted that Steeples and Jones did not envision a necessary connection between increased use of networks and knowledge gain. However, they did observe networked learning as one of the aspects of a networked society (Castells, 2000) that considers knowledge construction as related to the knowledge flow in networked settings (Steeples & Jones, 2002).

Illich (1971), when discussing learning webs and how educational institutions should develop, said that we need such relational structures that will enable each student to define themselves or herself by



learning and by contributing to the learning of others. In a somewhat broader context, Illich also argued that we should not start with the question “What should someone learn?” (p. 77), but rather with “What kinds of things and people might learners want to be in contact with in order to learn?” (p.78) highlighting (perhaps indirectly) the importance of interaction within a network of learners. More recently, Goodyear (2002) stressed the importance of moving beyond merely acknowledging the importance of the social context of individual learning and acknowledging that a learners’ cognitive activity will be influenced by interaction with their peers and teachers. This interaction and students’ ability to define themselves by learning should be depicted in the structure of the emerging network or networks. The tendency to form different types of connections should provide insight into the learning patterns in the network of learners and into the knowledge or more general information flow in networked learning settings. Finally, the importance of studying the emerging network structures could be implied from Fox’s (2002) argument that studying learning in networks should primarily focus on “identification of collaborative and competing networks and their characteristic learning patterns” (p.89) as ways of understanding how such networks learn.

### Discourse

Regardless of the educational setting, learning has been related to a certain form of student-generated artefacts (Jones, 2008; Wenger, 1998). Thus, studying learning in social settings, various researchers focused on analyzing student-generated discourse to examine the association between discursive activity and learning (Gee & Green, 1998). For example, arguing for a significant connection between knowledge and discourse, Ohlsson (1996) claimed that “human beings employ their understanding, not in action, but in the generation of symbols” (p. 51). Specifically, Ohlsson and more recently Goodyear (2004), discussed “understanding” as a key construct of learning in higher education, claiming that it is closely connected with the production of discourse.

Language and discourse further represent primary means of information exchange in computer-mediated communication, implying that the majority of (if not all) interactions are confined to the interaction with learning discourse—either brought into the learning space (e.g., textbooks, learning materials) or generated by students within it (artefacts) (Jones, 2008). This further means that to a certain extent, student’s peers “also appear through artefacts rather than in person” (Jones, 2008, p. 620). Finally, Stahl & Rosé (2011), among others, contended that language and discourse can provide a valuable insight into the learning dynamics and cognitive processes in social learning settings. Therefore, our model also argues for the importance of understanding *student-generated discourse* in order to provide more salient insights into the learning dynamics in a non-formal distance education context. Analyzing student discourse, we aim to observe linguistic indices of *student cognitive and affective engagement*, as defined by Reschly and Christenson (2012) and re-operationalized in learning in networks by Joksimović et al. (2016).

Student-generated discourse, however, should not be observed without accounting for particular social settings. As defined by Hicks (1995), the term *discourse* refers to the communication that is “socially situated and that sustains social ‘positionings’” (p. 49), implying that the understanding of the association between language and learning is possible only within a given social context. This perception of discourse as being inherently social is rooted in the work of Bakhtin (1986) and Vygotsky (1986), who made similar conclusions that the meaning of language can be operationalized only through social adoption. More recently, this thinking has been reflected in Gee and Green’s (1998) conceptualization of “situated meaning,” referring to the interpretation of discourse as context dependent. This notion of discourse as being socially situated is also depicted in our conceptual analytical model by considering two constructs—structure and discourse—as mutually dependent, whereas the emergence of both constructs and their mutual relationship have been mediated by contextual factors.

### *Dynamics*

The term learning has been used very broadly, with different meanings in various contexts (Illeris, 2004, 2007). However, regardless of the definition or the context, there is a single constant with respect to the concept of learning: *Learning is a process*. Therefore, learning theories are more concerned with a process of knowledge construction rather than “with the value of what is being learned” (Siemens, 2005, p. 2). In networked settings, learning is observed as a dynamic and complex process that involves student interactions (with other students, between students and teachers, and with content) and content creation (Goodyear, 2002; Halatchliyski, Moskaliuk, Kimmerle, & Cress, 2014). Finally, the networks emerging from interactions within non-formal education settings are not static by any means. As Halatchliyski et al. (2014) observed: “Networks are constantly changing as neither their nodes nor their links are enduring entities” (p. 102). Therefore, we tend to argue that failing to account for the temporal aspects of learning in MOOCs could lessen our understanding of learning processes in such settings.

### *Individual agency*

Learning in online and networked settings has created a shift in power between students and teachers (Steeple & Jones, 2002). Online learning transforms education from instructor centered (traditional classroom) to student centered, where students have more responsibility for their learning (Koch, 2014; Peterson, 2008). Given that students are able to choose what to learn, when to learn, and who to learn with, a certain level of self-directedness is necessary to succeed in an online course. With the emergence of open educational resources and MOOCs in particular, the importance of an individual student’s agency has become perhaps even more important. Learning in networks is inherently less structured than traditional (more formal) online courses. As noted in various studies, the easy and no-cost access to MOOCs usually attracts a large number of students to enrol, often without a real intent to complete the course but rather with diverse personal learning goals. Therefore, the conceptual analytical model

proposed in this work also accounts for *students' individual agency and contextual variables* that frame interactions in non-formal networked educational settings.

Our understanding of the importance of individual agency stems from social learning theories and an assumption that human behavior is guided by constant and “continuous reciprocal interaction between behaviour and its controlling conditions” (Bandura, 1977, p. 2). Thus, in his seminal work on social cognitive theory, Bandura (1977, 2001) posit that determinants which frame students' (or human in a more general context) behavior emerge from a constant interaction between personal, behavioral, and environmental (i.e., contextual) factors. The principle of reciprocal determinism - i.e., the product of the continuous interaction between the three factors (Bandura, 2001) - further assumes that students have an ability to modify their own behavior and environment in a meaningful manner (Bandura, 2001). Finally, Bandura's theory posits that learning is not necessarily demonstrated as an immediate change in a behavior. In the context of the original theory, personal (or cognitive factors) include cognitive abilities, physical characteristics, personal beliefs, and attitudes. Behavioural competencies, on the other hand, include self-efficacy, skills, and social interactions, among other factors, whereas environment is defined as a social (e.g., peers, friends) and physical (e.g., classroom) environment.

Our analytical framework provides further operationalization of the three components— *context*, *personal characteristics*, and *behavior* — with respect to non-formal educational settings. Specifically, **contextual analyses** account for the factors that define specific learning context and for the nature of the interaction between two or more individuals in a social network that is derived from a collective behavior. **Personal characteristics** include students' demographic data, motivational factors, and previous experience, among others. Finally, **behavioral variables** describe behavioral and cognitive aspects of students' engagement within a given course, as defined described Reschly and Christenson's (2012) model of association between context, engagement, and learning outcomes and re-operationalized within the context of MOOCs in the work by Joksimović et al. (2016).

## Defining a Task Model

In the conceptual assessment framework, the task model defines the environment in which students exhibit the knowledge, skills, and abilities identified in the student model (Mislevy, 1994). Specifically, it enables us to identify a set of tasks and conditions necessary for assessing student model constructs. One of the important aspects of the task model definition is describing situations (i.e., tasks and conditions) in terms of the *presentation format* (concrete specifications of the environment), and *work product* (a form that will capture student performances) (Mislevy, 1994; Mislevy et al., 2003).

In the empirical validation of the proposed analytical model, we analyzed students' learning in a variety of contexts (e.g., Joksimović, Dowell, et al., 2015; Joksimović, Kovanović, Jovanović, et al., 2015; Skrypnyk, Joksimović, Kovanović, Gasšević, & Dawson, 2015). Given the specific nature of research in non-formal digital educational settings and MOOCs in particular, there is no single environment that allows for evoking evidence about focal constructs (the knowledge, skills, and abilities) defined in the student model. Rather, the environments used to deliver MOOCs are designed to scale up to support a large number of students, which in turn allows for large-scale data collection (Daniel, 2012; DeBoer et al., 2014). Nevertheless, regardless of the platform used to deliver a course—a structured version using edX or Coursera or a distributed context using social media—all those environments should allow for data collection in a form of trace (log) data, discussion forum data, surveys, and/or assessment result, to name a few. This further implies that a concrete *list of tasks*, their *characteristics and variable features*, heavily depends on a specific instructional course design and applied pedagogies for teaching and learning.

Learning in non-formal digital educational settings is also characterized by a variety of potential *task products* that provide evidence for the student model constructs. These are related to the quality of student postings in a discussion forum, engagement with course content, or patterns of social media use, to name a few. In our work, we concentrate primarily on the data collected by various learning (or social media) platforms. This approach represents an unobtrusive way of data collection and does not require interruption of student behavior. However, the data collection methods could be easily extended to account for perhaps more sophisticated approaches, including multimodal data sources (e.g., eye movement, heart rate).

## Evidence Model-Operationalization of the Conceptual Analytical Model

The third element of the conceptual assessment framework is the evidence model, a model that bridges a student and a task model (Mislevy & Haertel, 2006). An evidence model provides detailed guidelines for how information about student model constructs should be updated based on specific work products and obtained from particular tasks (Mislevy et al., 2003). There are two building blocks of every evidence model: an evaluation component (i.e., evidence rules) and a measurement model (Mislevy et al., 2003; Mislevy & Haertel, 2006). The evaluation component specifies a procedure for identifying and evaluating observable variables from the student model. The measurement model, on the other hand, synthesizes evaluation results across different tasks, forming comprehensive insight into student learning.

To inform the design of the evidence model, in the proposed conceptual assessment framework we conducted comprehensive research on educational variables that are commonly used to measure

learning in MOOCs (Figure 1 and Appendix). A main challenge in defining our evidence model was interpreting learning in nonformal educational settings relying on traditional educational metrics. Specifically, contemporary research on learning in MOOCs argues for two main differences between learning in a traditional classroom setting and in networks. The primary difference is related to the nature and scale of gathered data, which are significantly higher than in more traditional learning settings (either online or face to face) (DeBoer et al., 2014; Evans et al., 2016). Second, learners in networked settings are diverse in many aspects—such as their backgrounds, intents, and reasons to register for a course (DeBoer et al., 2014; Reich et al., 2016). Therefore, we conducted a systematic literature review with a main goal of identifying the common metrics used to assess learning in MOOCs, as well as how various researchers have measured learning outcomes in this particular setting (Joksimović et al., 2016). Besides summarizing metrics used to measure and model learning in non-formal educational context, we also developed a framework that distinguishes between the factors impacting students' learning in MOOCs. Specifically, building on Reschly and Christenson's (2012) model of the associations between context, engagement, and student outcomes, we further re-defined and re-operationalized these constructs (i.e., context, engagement, and out-come) for learning in non-formal, digital educational settings, providing a potential framework for interpretation, and contextualization of the observed variables from the student model.

## Discussion and Future Work

Research on MOOCs is a relatively new field of inquiry that has proliferated in recent years (Raffaghelli, Cucchiara, & Persico, 2015). The research shows maturation of the field with diverse research paradigms having been adopted, varying from data driven to conceptual and theoretical (Raffaghelli et al., 2015). Nevertheless, the majority of studies in non-formal, digital educational settings focus primarily on observational and critical research methods, failing to provide more sustainable evidence of factors influencing learning in such settings (Raffaghelli et al., 2015; Reich, 2015).

This research contributes to the development of the next generation of research in networked settings (Reich, 2015). Following the ECD framework, we developed a conceptual analytical model for assessing learning in MOOCs, proposing definitions of the learning-related constructs that form the model, along with their mutual relationships, operationalisations for the measurement of those constructs, and automated methods that can scale up the applicability of the proposed model. Such a conceptual model should provide a common framework for the more advanced research in MOOCs so that more significant implications for teaching and learning can be obtained.

Our current research provides evidence of how the proposed conceptual model establishes a comprehensive picture of learning in networked settings, as well as why it is important to consider the

elements of the model as interdependent. Specifically, through the empirical research we proposed novel analytical methods for studying learning in non-formal educational settings, accounting for the quality of student-generated discourse, specific factors that drive interaction in such settings, as well as the temporal dynamics of discourse and structure development (e.g., Joksimović, Dowell, et al., 2015; Joksimović, Kovanović, Jovanović, et al., 2015; Skrypnyk et al., 2015). Finally, our research showed that in order to make meaningful interpretations of learning outcomes, it is necessary to account for specific contextual factors that frame social interactions in a given context (Joksimović et al., 2016).

Further work is primarily concerned with providing a framework for making inferences about learning based on the developed conceptual model. Currently, the model identifies the important learning-related constructs and proposes a relationship between those constructs, theorizing how they might help to explain learning in MOOCs. However, we aim to build a statistical model that would allow for testing the association between the various measures of learning in networked settings and the constructs of the theorized model. Such a statistical model will provide a sound basis for understanding factors that promote learning in MOOCs and provide a means for comparisons to be made to other settings (e.g., face to face or online).

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## Appendix: Design Pattern

Author	
First Name	Srećko
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Overview	
Summary	<ul style="list-style-type: none"> <li>Studying <i>learning</i> in nonformal educational settings needs to account for specificities of learning in networks as well as for students' individual agency.</li> <li>A comprehensive understanding of learning in networked settings could be obtained through analysis of the <i>structure</i>, <i>discourse</i>, and <i>dynamics</i> of social interactions.</li> <li>Learning in networks is inherently less structured than in traditional (more formal) courses. Therefore, <i>students' individual characteristics and environmental variables</i> should be observed as factors that frame interactions in non-formal networked educational settings.</li> <li>As a most prominent form of delivering planned learning (at scale) in networks, here we focus on massive open online courses (MOOCs).</li> <li>Emergence of MOOCs influenced the development of digital learning environments that would support large numbers of students enrolling and store the immense amount of data related to their participation and interaction.</li> <li>The data collected by these systems can include information about student background, intents, or various forms of engagement within learning environments, to name a few.</li> </ul> <p>Bandura, A. (2001). Social cognitive theory: An agentic perspective. <i>Annual Review of Psychology</i>, 52(1), 1–26.</p> <p>DeBoer, J., Ho, A. D., Stump, G. S., &amp; Breslow, L. (2014). Changing “course”: Reconceptualizing educational variables for massive open online courses. <i>Educational Researcher</i>, 43(2), 74–84.</p> <p>Goodyear, P. (2002). Psychological foundations for networked learning. In C. Steeples &amp; C. Jones (Eds.), <i>Networked learning: Perspectives and issues</i> (pp. 49–75). New York, NY: Springer-Verlag New York, Inc. Retrieved from <a href="http://dl.acm.org/citation.cfm?id=571334.571339">http://dl.acm.org/citation.cfm?id=571334.571339</a></p> <p>Joksimović, S., Manataki, A., Gašević, D., Dawson, S., Kovanović, V., &amp; de Kereki, I. F. (2016). Translating network position into performance: Importance of centrality in different network configurations. In <i>Proceedings of the Sixth International Conference on Learning Analytics &amp; Knowledge</i> (pp. 314–323). New York, NY: ACM. <a href="http://doi.org/10.1145/2883851.2883928">http://doi.org/10.1145/2883851.2883928</a></p> <p>Joksimović, S., Poquet, O., Kovanović, V., Dowell, N., Caitlin, M., Gašević, D., ... Graesser, A. C. (2016). How do we model learning in massive open online courses? A systematic literature review. Manuscript in preparation.</p>
Rationale	<ul style="list-style-type: none"> <li>Although research in learning analytics in general and learning analytics for MOOCs in particular have attained significant attention, most of the current studies that investigate learning in traditional online and non-formal educational settings fail to account for existing learning theories.</li> <li>MOOC research is commonly critiqued for being primarily observational in nature and failing to provide causal relationships between observed metrics of student engagement in networked settings and learning.</li> <li>Moreover, learning in non-formal educational settings differs from that in more traditional forms of education in many aspects (e.g., the magnitude and format of data about students' learning, diversity of students' background, intents, or socioeconomic status).</li> <li>The main goal of this research is therefore to advance learning analytics methods for assessing learning quality in non-formal digital educational environments.</li> </ul> <p>Proposing definitions of the learning-related constructs that form the model of learning in networks, along with their mutual relationships, operationalisations for the measurement of those constructs, and automated methods that can scale up the applicability of the proposed model, should provide a common framework for more advanced research in MOOCs, so that significant implications for teaching and learning can be obtained.</p>

Student Model	
<b>Focal construct</b>	<ul style="list-style-type: none"> <li>Learning in non-formal distance educational settings. <ul style="list-style-type: none"> <li><i>Structure</i> of students' social interactions explains the regularities in communication between peers and instructors, revealing main (social and technical) factors that frame this interaction and influence learning processes.</li> <li>Student-generated <i>discourse</i> provides further insight into the quality of learning. Relying mainly on linguistic indicators of text cohesion and coherence, the construct explains the level of students' cognitive and affective engagement, as well as a comprehension of learning materials.</li> <li><i>Dynamics</i> examines the importance of the temporal dimension for the association between students' activity and learning. It also accounts for the development of the behavioural variables.</li> <li>To properly describe the learning environment and allow for comprehensive interpretation of the focal construct, studying learning in networks also accounts for <i>contextual</i> factors, <i>behavioural</i> factors, and metrics that describe students' <i>personal characteristics</i>.</li> </ul> </li> </ul>
<b>Additional knowledge, skills, and abilities</b>	<ul style="list-style-type: none"> <li>Self-efficacy</li> <li>Metacognitive knowledge</li> </ul>
Task Model	
<b>Characteristic features of the task &amp; Variable features of the task</b>	<ul style="list-style-type: none"> <li>Given the specific nature of the research in non-formal digital educational settings (and MOOCs in particular), there is no single environment that allows us to evoke evidence about focal constructs (i.e., knowledge, skills, and abilities) defined in the student model. Rather, the environments used to deliver MOOCs are designed to scale up to support a massive number of students and allow large-scale data collection.</li> <li>Nevertheless, regardless the underlying platform used to deliver a course, all those environments should allow for data collection in a form of trace (log) data, discussion forum data, surveys, and/or assessment result, to name a few.</li> <li>This further implies that a concrete <i>list of tasks</i>, their <i>characteristics</i>, and <i>variable features</i> heavily depend on a specific instructional course design and applied pedagogies for teaching and learning.</li> </ul>
<b>Potential task products</b>	<ul style="list-style-type: none"> <li>Learning in non-formal digital educational settings is also characterized by a variety of <i>potential task products</i> that provide evidence for the student model constructs. These are related to <ul style="list-style-type: none"> <li>the quality of student postings in a discussion forum,</li> <li>engagement with course content, or</li> <li>patterns of social media use, to name a few.</li> </ul> </li> </ul>
Evidence Model	
<b>Potential observations</b>	<p>A limited list of (broadly defined) potential task products includes measures of</p> <ul style="list-style-type: none"> <li>academic engagement,</li> <li>behavioral engagement,</li> <li>cognitive engagement,</li> <li>affective engagement, or</li> <li>contextual variables.</li> </ul>
<b>Potential frameworks</b>	<ul style="list-style-type: none"> <li>Extract features based on discourse properties, social-dynamic dimensions that frame social interactions in a given context, students' engagement within a given environment, and student data in order to build models to assess learning quality during course progression.</li> </ul>

## 2.3 Summary

### 2.3.1 More on the model constructs

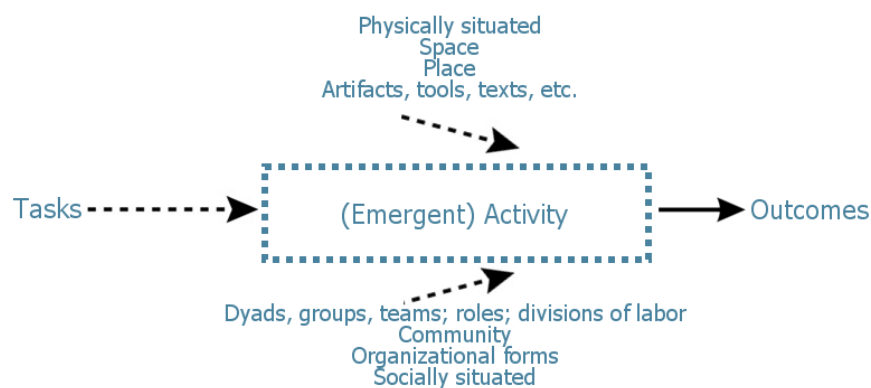
The main contributions of this chapter are i) an overview of the fundamental conceptualizations adopted throughout my research and ii) a conceptual analytics-based model for studying learning networks emerging from learning with MOOCs, thus providing a framework for the remaining chapters. The model recognizes three central elements that should be observed in order to obtain a comprehensive portrait of learning networks – *structure* of interactions in a given contexts (Illich, 1971; Castells, 2000; Steeples and Jones, 2002; Fox, 2002; Eynon *et al.*, 2016; Goyal, 2002), *discourse* produced as a result of those interactions (Goodyear, 2002; Jones, 2008; Ohlsson, 1996; Gee and Green, 1998), and *dynamics* of learning processes (Halatchliyski *et al.*, 2014; Goyal, 2002). The three elements should be observed as interdependent constructs, in order to examine how social interaction factors shape discourse properties, as well as how temporal dynamics frame network structural properties and influence development of discourse (Section 2.2).

The proposed model heavily draws on the existing networked learning research. As argued by Goodyear and Carvalho (2014b), “learning networks need to be a focus for networked learning research because of the idea of indirect design, a key theoretical contribution of networked learning” (Jones, 2015, p.12). The notion of indirect design assumes that learning “cannot be designed directly and that it can only be designed for” (Jones, 2015, p.12). Therefore, to identify elements that could potentially explain learning in networks, I rely on some of the critical perspectives and pedagogical values emerging from a broad area of inquiry in formal and informal learning settings. However, given that the main aspect of my research introduces novel analytics methods that would allow for the assessment for learning (Knight *et al.*, 2013), I grounded the operationalization of the proposed constructs in the multidisciplinary field of learning analytics.

Although the current literature typically adopts a social approach to understanding learning networks, it also accounts for “the individual in their social and material context” (Goodyear and Carvalho, 2014a, p.58). Therefore, building further on the research in social and learning sciences, the proposed model for studying learning networks relies on premises of social cognitive theory and Bandura’s (1977; 1986) work. Specifically, the analytics-based model proposed in this chapter accounts for contextual, behavioral, and personal characteristics to (i) comprehensively describe the learning environment, learning context, and learners, and (ii) enable for a holistic interpretation of the model constructs and their relationships. Thus, the contextual analysis accounts for the factors that define the specific learning context and the nature of interaction between two or more individuals in a social network that is derived from the collective behavior (Bandura, 1977). Personal characteristics include students demographic data, motivational factors, and previous experience, among others (Bandura, 1977, 1986). Behavioral variables primarily describe aspects of students’ academic and behavioral engagement within a given course (Section 3.2).

### 2.3.2 Design & Assessment for Learning

Being framed around the notion of assessment for learning, the analytics-based model proposed in this chapter is also aligned with (or perhaps complements) the activity-centered approach to design and analysis proposed by [Goodyear and Carvalho \(2014a\)](#) ([Figure 2.1](#)). The activity-centered approach to the analysis of learning situations focuses on “*what it is that people are actually doing*” ([Goodyear and Carvalho, 2014a](#), p.58), as well as what social interaction and resources are being utilized in this activity. Therefore, [Goodyear and Carvalho \(2014a\)](#) framework defines *activity* as a key construct that determines learning in networks. Activity further mediates the association between tasks, tools, and resources and between interpersonal relationships and learning outcome. In my thesis, I make an attempt to quantify activity through *engagement*, that can be observed as a mediating factor between contextual elements and learning outcome, as will be outlined further in [Chapter 3](#). In so doing, my focus is on developing learning analytics methods that would potentially assist teachers and learners in obtaining more comprehensive insights into learning to regulate learning activities accordingly, without necessarily focusing on design activities as [Goodyear and Carvalho \(2014a\)](#) do in their framework.



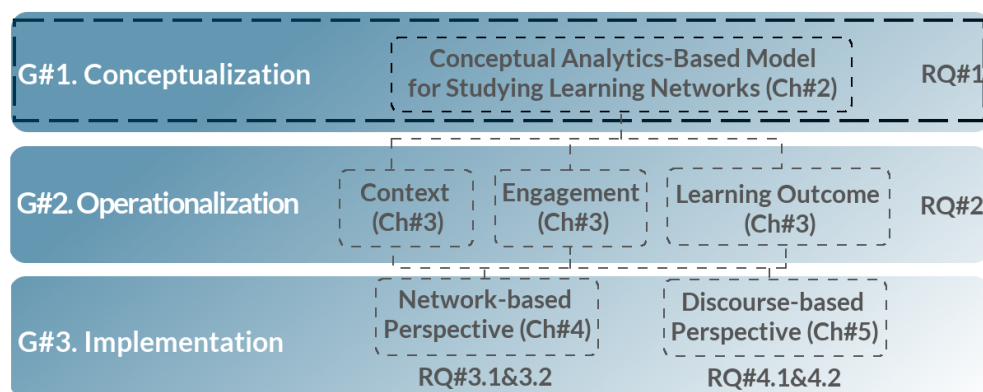
**Figure 2.1.** Activity-centered approach to learning design, adopted from [Goodyear and Carvalho \(2014a, p.59\)](#).

[Goodyear and Carvalho \(2014a\)](#) further recognize the following five attributes of activity: (i) activity is *ongoing* and its “normal state is in motion” (*ibid.*, p.58), (ii) activity is often oriented towards a certain goal, (iii) activity is shaped by contextual factors in which it unfolds, (iv) learners’ individual activities are often influenced by activities of their peers, and (v) performed activities are influenced by existing social norms and rules. I tend to argue that these five attributes of the activity, as defined by [Goodyear and Carvalho \(2014a\)](#), are also captured within the analytics-based model proposed in the present thesis. Specifically, the proposed conceptual analytics-based model argues for the importance of considering temporal dynamics of learning networks as one of the key constructs. Observing structure and discourse along with their mutual relationship, my model also provides insight into how learning unfolds and to what extent learners’ activities are influenced by their peers ([Section 4](#) and [Section 5](#)). Finally, accounting for learners’ individual agency and contextual factors, the proposed

analytics-based model also provides insights into how personal goals, motivation or interests, as well as “physical settings” (Goodyear and Carvalho, 2014a, p.59) in which learning occurs, shape learners’ engagement and learning in networked settings.

### 2.3.3 Chapter summary and moving forward

In this chapter, I introduced a conceptual analytics-based model for studying learning networks emerging from learning with MOOCs (Figure 2.2). Being established in the ECD framework for designing educational assessments (Mislevy *et al.*, 2003), the proposed conceptual model lays a foundation for the remaining work presented in this thesis, providing a comprehensive understanding of learning networks at individual and network levels. Specifically, the study introduced in Section 2.2, outlines key elements of the assessment design that include student, evidence, and task models. The student model provides detailed definitions of the focal constructs that should be observed in order to analyze learning networks. Specifically, to provide comprehensive understanding of learning networks, it is necessary to account for structure of learner interactions, discourse generated in the learning process, and temporal dynamics of structural and discourse properties. These three elements – structure, discourse, and dynamics – should be observed as mutually dependent, taking into account learners’ personal interests, motivation, behavior, and contextual factors that determine the environment in which a specific learning network develops (Section 2.2).



**Figure 2.2.** Overview of the thesis structure across the three main goals identified in the present research, with the highlighted focus of the second chapter.

*Evidence model*, on the other hand, outlines a potential operationalization of the key constructs introduced in the student (i.e., conceptual) model. However, the present chapter does not go beyond simply stating that the fundamental dimensions of learning networks should be measured relying on the construct of learners’ engagement. Therefore, as outlined in Figure 2.2, the next chapter (Chapter 3) provides a detailed operationalization of the engagement construct in the context of learning networks emerging from learning with MOOCs.

Finally, in defining the *task model*, it is not my intent to identify an all-encompassing and definitive list of tasks and environments that would allow networked learners to elicit different forms of

engagement. It is questionable to what extent such goal would be realistic given a wide range of available technologies that allow for designing for learning in networks, ranging from various social media (e.g., Twitter, Facebook, blogs) to more structured environments (e.g., edX or Coursera) (Belleflamme and Jacqmin, 2015; Kay *et al.*, 2013). Therefore, through the five empirical studies introduced in the second part of the thesis (Chapter 4 and Chapter 5), I account for different educational settings and focus on three broad categories of tasks – (i) network-related, such as network building or network awareness, (ii) knowledge artefacts-related, observed through viewing navigating, organizing, and creating knowledge artifacts, and (iii) discourse-related, as viewing or contributing to the generated discourse.



## Model Operationalization – Engagement and Learning Networks

### 3.1 Preface

The previous chapter ([Chapter 2](#)) focuses on identifying learning-related constructs, along with their mutual relationships, that would provide comprehensive understanding of learning networks emerging from social and socio-technical interactions in MOOCs. As such, [Chapter 2](#) also highlights the importance of providing an operationalization of the proposed constructs and establishing a basis for developing learning analytics methods for assessment for learning in the context of learning networks. This chapter, on the other hand, focuses on addressing the second goal of my thesis in formulating observable evidence that would provide insights into the fundamental elements of learning networks (i.e., discourse, structure, and dynamics). In so doing, I focus on engagement as a theoretical model for explaining factors that potentially contribute learning and predicting learning success. Observed through the notion of *design for assessment*, I build on the concept of engagement in order to understand process and outcome of *emergent activities* ([Goodyear and Carvalho, 2014a](#)).

The core of this chapter is framed around the study that presents a systematic literature review of approaches to model learning in MOOCs and offers a operationalization of the engagement construct in learning networks emerging from learning with MOOCs ([Section 3.2](#)). However, before elaborating on the proposed engagement framework, I briefly review commonly applied approaches to the study of engagement in online educational settings in general ([Section 3.1.1](#)). [3.1.3](#) further provides a detailed overview of the existing approaches to measuring engagement in MOOCs and highlights the importance of redefining this complex construct in the context of learning networks, primarily those emerging from MOOCs as the primary context for the study of learning networks in the present thesis. Finally, in [Section 3.4](#), I provide a more detailed overview of the association between the constructs of the model introduced in [Chapter 2](#) and the engagement model presented in [Section 3.2](#).

#### 3.1.1 Learning & Engagement Revisited

Student engagement attained significant attention in higher education research and practice, aiming at enhancing learning and teaching, primarily in traditional face-to-face settings ([Trowler, 2010](#); [Christenson et al., 2012](#)). Research on engagement has its roots in Astin's (1984) seminal work on student involvement. However, it was in mid 90s when the term "engagement" was introduced as most commonly understood today ([Trowler, 2010](#); [Christenson et al., 2012](#)). Very quickly, educational research provided a considerable amount of work that showed a significant association between students' involvement in learning-related activities and course outcome or dropout ([Trowler, 2010](#)). Nevertheless, although existing research in general agrees that student engagement should be observed as a multidimensional construct, there is no clear agreement on the number and definition of underlying dimensions of engagement.

In addition to the behavioral engagement, as a most commonly accepted operationalization, researchers also argue that the conceptualization of engagement should more formally account for students emotion and cognition ([Fredricks et al., 2004](#); [Appleton et al., 2006](#); [Reschly and Christenson, 2012](#);

Christenson *et al.*, 2012; D'Mello *et al.*, 2017). Moreover, there is a tendency to divide behavioral engagement into two subtypes, observing behavioral (e.g., participation) and academic (e.g., time on task) as separate constructs that comprise student engagement (Christenson *et al.*, 2012). Recently, a specific form of engagement – i.e., an *agentic engagement* (Reeve and Tseng, 2011) – emerged as a form of explaining learners' contribution to the learning process (Sinatra *et al.*, 2015; D'Mello *et al.*, 2017). Finally, besides observing engagement as either process or outcome, different perceptions of engagement observe this multifaceted construct either on a single continuum (low and high engagement) or whether engagement and disengagement are observed at separate continua (Christenson *et al.*, 2012; Appleton *et al.*, 2006).

More recently, proliferation of MOOCs and online learning in general, brought new promises as well as new challenges to the educational research. Bringing learning at scale and providing education to the unprecedented number of students, MOOCs have been seen as a most prominent way in transforming education (Haggard *et al.*, 2013; Daniel, 2012). However, MOOCs have been also criticized for the problem of low student motivation and engagement that resulted in rather limited social interaction with peer learners and low completion rates (Kovanović *et al.*, 2015). Thus, mostly relying on the construct of engagement, however, often without even making an attempt to define it or build on some of the existing research in more traditional learning settings (DeBoer *et al.*, 2014; Ramesh *et al.*, 2014b; Azevedo, 2015).

### 3.1.2 Engagement in MOOCs - current conceptualization

Most of the existing research in MOOCs observes forum participation, interaction with course materials (e.g., videos or lectures), and participation in assessment activities as means for operationalization of engagement with learning at scale (Ramesh *et al.*, 2014b; Tucker *et al.*, 2014; Sinha and Cassell, 2015; Santos *et al.*, 2014). These engagement-related metrics are usually being extracted from a single course, delivered using the Coursera or edX platforms, with 10,000 or less students who actively participated in a course (for details see Section 3.2). The primary means for extracting different engagement metrics is to explore factors that could predict learning outcome or course persistence (Wang *et al.*, 2015; Adamopoulos, 2013).

Usually referred to as a *discussion behavior* (Wang *et al.*, 2015), *behavior* (Ramesh *et al.*, 2014a,b), or *engagement* (Santos *et al.*, 2014; Tucker *et al.*, 2014; Sinha and Cassell, 2015), various researchers tended to observe engagement-related metrics from a single perspective operationalized through students' participation in different activities. Specifically, researchers tend to measure engagement as a form of participation in discussion forums (quantity of contribution) (Wang *et al.*, 2015; Vu *et al.*, 2015), watching video lectures (Li *et al.*, 2014, 2015), or participating in course assessment activities (Ye *et al.*, 2015; Whitehill *et al.*, 2015). Several studies also focus on the quality of contribution in discussion forums, either as a single perspective or perhaps as an extension of the analyses that observed quantity of forum participation (Yang *et al.*, 2014; Wang *et al.*, 2015). The overarching understanding is that more

active engagement with the course content and more intensive interaction with peer learners leads to higher course grades, better learning gain achievement and increased course persistence.

Several researchers, however, moved beyond observing a single source of evidence to operationalize engagement in MOOCs as a complex, multidimensional construct. Ramesh and colleagues (2014a; 2014b), for example, defined engagement in learning at scale as a complex interaction between behavioral, linguistic, and social cues that spans across the three types of latent variables that represent active engagement, passive engagement, and disengagement. Ramesh and colleagues further showed that the model based on the three latent variables provides better prediction accuracy for student course success, than it was the case with the individual measures, such as number of video watched, number of messages posted or viewed, to name a few. Although very comprehensive, it is still questionable to what extent such a model provides a connection with existing research on student engagement in different educational settings, as well as to what extent it could generalize across different MOOC domains.

### 3.1.3 Importance of scaling engagement

As briefly outlined in the previous sections, one of the main challenges for researching engagement in MOOCs is the lack of common understanding how engagement should be defined and measured in the context of learning at scale (Section 3.2). Having a generally accepted conceptualization of engagement would allow for obtaining more comprehensive insight into the factors that influence learning with MOOCs as well as how these factors could be generalized across different platforms or compared with diverse context (such as traditional online or face to face learning) (DeBoer *et al.*, 2014; Evans *et al.*, 2016). Moreover, it would allow for moving beyond observing student “click data” and exploring how quantity and quality of interactions with the course content or peers could predict course outcome and persistence.

It is rather typical that researchers simply refer to a construct of engagement without necessarily considering different dimensions of this complex concept (Santos *et al.*, 2014; Sinha and Cassell, 2015; Tucker *et al.*, 2014; Ramesh *et al.*, 2014b). It is, however, necessary to understand that “when measuring one dimension of engagement, the other [dimensions of engagement] are likely contributing to that evaluation” (Sinatra *et al.*, 2015, p.3). Although very informative, from the perspective of providing insights into the factors that could influence learning in a given context, such studies do not necessarily provide a basis for establishing sound connection with existing learning theories (Reich, 2015; DeBoer *et al.*, 2014; D’Mello *et al.*, 2017). For example, it is not always clear why posting to a discussion forum or watching a video should be beneficial for learning. My understanding, therefore, aligns with ideas highlighted by Sinatra *et al.* (2015) or D’Mello *et al.* (2017), who, among others, pointed out the importance of simultaneous and convoluted measurement of multiple dimensions of engagement in order to provide salient understanding of the association between engagement and learning in a wide variety of educational settings.

With the development of learning analytics research and emergence of large scale data collected about student learning, various researchers are highlighting the importance of building research based on the sound theoretical assumptions, rather than simply relying on big data to explore factors that contribute to learning (Wise and Shaffer, 2015; Dawson *et al.*, 2015; Gašević *et al.*, 2016). Moreover, Gašević and colleagues (2016) also stress the importance of considering contextual factor when trying to predict learning outcome or course persistence. Framing their research around the Winne and Hadwin (1998) model of self-regulated learning, Gašević and colleagues (2016) showed how instructional conditions, as an important component of external conditions, affect the interpretation of learning-related measures.

For the purpose of identifying measures that provide operationalizations of the constructs introduced in the conceptual analytics-based model presented in Chapter 2, I therefore rely on the conceptualization of the association between context, engagement, and learning outcome as proposed by Reschly and Christenson (2012). Specifically, in the following section, I introduce a publication that proposes a redefinition and re-operationalization of the engagement model for the study of engagement in MOOCs by building on the previous work in the traditional learning settings. The original framework (Reschly and Christenson, 2012) observes engagement as a complex construct comprised of academic, behavioral, cognitive, and affective engagement that mediate the association between the context in which learning occurs and learning outcome. This redefinition of the association between the context, engagement, and learning outcome in the context of learning at scale, informed further the elements of the *evidence model*, as introduced in Chapter 2. Section 3.2 further elaborates how various aspects of the evidence model inform definition of the *task model* and list of the potential environments and task products that allow students to express different aspects of engagement in the context of learning networks.

### 3.2 Publication: How do we model learning at scale?

The following section includes the copy of the following publication that was submitted for the second round of review:

Joksimović, S., Poquet, O., Kovanović, V., Dowell, N., Caitlin, M., Gašević, D., Dawson, S., Brooks, C., Graesser, A. C. (2017, *under review*). How do we Model Learning at Scale? A Systematic Review of the Literature. Review of Educational Research

# How do we Model Learning at Scale? A Systematic Review of the Literature

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## **Abstract**

Despite a surge of empirical work on student participation in online learning environments, the causal links between the learning-related factors and processes with the desired learning outcomes remain unexplored. This study presents a systematic literature review of approaches to model learning in Massive Open Online Courses offering an analysis of learning related constructs used in the prediction and measurement of student engagement and learning outcome. Based on our literature review, we identify current gaps in the research, including a lack of solid frameworks to explain learning in open online setting. Finally, we put forward a novel framework suitable for open online contexts based on a well-established model of student engagement. Our model is intended to guide future work studying the association between contextual factors (i.e., demographic, classroom, and individual needs), student engagement (i.e., academic, behavioral, cognitive, and affective engagement metrics) and learning outcomes (i.e., academic, social, and affective). The proposed model affords further inter-study comparisons as well as comparative studies with more traditional education models.

**Keywords:** Non-formal education, learning environments, MOOCs, engagement

Massive Open Online Courses (MOOCs), as one of the most prominent ways for facilitating learning at scale, have now been part of the educational landscape for almost a decade. The volume of learners enrolling in MOOCs generated widespread interest among the public, popular press, Government, social and education commentators (Reich, Stewart, Mavon, & Tingley, 2016). Some stakeholders expressed their belief in the groundbreaking effect MOOCs may have on higher education, possibly making traditional brick-and-mortar universities obsolete (Shirky, 2013). Alongside the touted potential of MOOCs, professionals in educational technology have expressed concerns about widely applied outdated pedagogical models integrated in many of the MOOCs. Despite a polarized debate (Selwyn, Bulfin, & Pangrazio, 2015), student enrollment numbers and course offerings continued to grow (Jordan, 2015a; Shah, 2015). This has resulted in a dearth of interest from researchers and, within a relatively short time frame, we have witnessed a substantial number of research studies and reports on MOOCs (Jordan, 2015b), as well as the formation of two annual MOOC-related scholarly conferences (Haywood, Aleven, Kay, & Roll, 2016; Siemens, Kovanović, & Spann, 2016).

Research has largely focused on students' persistence in MOOCs and the development of models to predict dropout or academic performance. Despite the volume of work to date, commentators have criticized such research as being primarily observational and lacking appropriate rigor. Reich (2015), for example, asserted that MOOC research has failed to provide causal linkages between the observed metrics and student learning, despite the vast amount of data collected on student activity within MOOCs. This limitation is in part due to the lack of theoretically-informed approaches employed in the analysis of MOOCs. Institutional reports on MOOC provisions as well as special issues on MOOCs have offered some insight into engagement during learning with MOOCs, but have presented little (or no) evidence of the factors contributing to learning *per se* (DeBoer, Ho, Stump, & Breslow, 2014; Reich, 2015).

The limited insight offered by the research thus far can be attributed to a general lack of understanding that non-formal educational settings, such as MOOCs (Walji, Deacon, Small, & Czerniewicz, 2016), differ from those of more traditional forms of education in many aspects. Technology and economies of scale allows for designing courses for unparalleled numbers of students and in ways that were not available in more traditional forms of learning (The Economist, 2014). Thus, some of the recent reports indicate that more than 58 million of students enrolled at least with one almost 7,000 MOOCs, offered by more than 700 universities (Shah, 2015). Students' interactions in such contexts further result in a magnitude and formats of data about learning that is stored within different platforms that substantially differ to traditional face-to-face or online learning practices (DeBoer et al., 2014; Evans, Baker, & Dee, 2016). The diversity of students represented in MOOCs is also unprecedented. The range in diversity is reflected in students' cultural backgrounds, socioeconomic



and employment status, educational level, and importantly, their motivations and goals for registering in a particular course (DeBoer et al., 2014; Glass, Shiokawa-Baklan, & Saltarelli, 2016; Reich et al., 2016). Therefore, DeBoer et al. (2014) and Evans et al. (2016) among others, have argued that MOOCs require a “re-operationalization and reconceptualization” (p.2) of the existing educational variables (e.g., enrollment, participation, achievement) commonly applied to conventional courses.

This study concurs with the argument by DeBoer and colleagues (2014) and posits that a more holistic approach is needed to understand and interpret learning-related constructs (observed during learning) and their association with learning (outcomes). These learning-related constructs are often observed under the broader concept of *learning* – a term commonly applied across a range of contexts with multiple interpretations and definitions (Illeris, 2004, 2007). Conceptually, learning refers to both (1) a complex multilevel process of changing cognitive, social and affective aspects of the self and the group, as well as (2) the outcomes of this process observed through the cognitive, social and/or affective change itself. Distinguishing between the process and the outcomes of learning, along with the contextual elements, is essential when modeling the relationships between them.

The necessity to redefine existing educational variables within new contexts originates from the concept of validity in educational assessment (Moss, Girard, & Haniford, 2006). Validity theories in educational measurement have been primarily concerned with a(1) standardized forms of assessment (e.g., tests); (2) providing a framework for interpretations of assessment scores in a given learning environment; and (3) making decisions and taking actions to support and enhance students’ learning (Moss et al., 2006). However, aiming to take a more pragmatic approach to validation, Kane (1992, 2006) posited that performance assessment should not be restricted to “test items or test-like tasks” (Kane, 2006, p.31). Evaluation of students’ performance can include a wide variety of tasks, performed in different contexts and situations (Kane, 2006). To be able to make valid interpretations of it is necessary to have a clear understanding how evaluation metrics have been defined for a given learning environment and its students (Kane, 2006, 2012; Moss et al., 2006).

This study contributes to the development of the “next generation of MOOC research” (Reich, 2015, p. 34) that can aid in explaining the learning process and the factors that influence learning outcomes. The present study critically examines how learning-related constructs are measured in MOOC research, and re-operationalizes commonly used metrics in relation to the specific educational variables within (1) learning contexts; (2) learning processes (i.e., engagement), and (3) learning outcomes. The study is framed in Reschly and Christenson’s (2012) model of the association between context, engagement, and outcome. Reschly and Christenson (2012) defined engagement as both a process and an outcome, therefore aligning the concept of engagement with a broader understanding of learning. In their work, Reschly and Christenson (2012) observed four aspects of student engagement: academic, behavioral,

affective and social. The authors conceptualized these as mediators between contextual factors, such as student demographics or intentions, and learning outcomes. Thus, we first examine commonly used learning-related metrics through a systematic review of the literature between 2012 and 2015 inclusive. We then analyze these metrics of observed student activity in light of Reschly and Christenson's (2012) model of associations between context, engagement, and student outcomes. Reschly and Christenson's (2012) model stems from the work on dropout prediction and increasing school completion, observing engagement on a continuum scale (ranging from low to high). By discussing the metrics representing the outcomes and indicators of learning within Reschly and Christenson's model, we demonstrate limitations and strength of current approaches to measuring learning in MOOCs. We then highlight differences that emerge between the Reschly and Christenson model and open online settings, to propose a modified operationalization of how learning in MOOCs can be studied.

We refer to MOOCs as planned learning experiences within *non-formal, digital* educational settings, used to facilitate learning at scale. In computer-mediated (networked) settings, as is the context of our research, learning is observed as a dynamic and complex process. Learning, involves student interactions with other students, teachers, and content (Goodyear, 2002; Halatchliyski, Moskaliuk, Kimmerle, & Cress, 2014). By *non-formal*, we assume any systematic learning activity conducted outside the formal/institutional settings (Eraut, 2000); in MOOCs such activity occurs within the structure prepared by the instructor but is heavily influenced by learner's motivations, actions, and decisions. Finally, *digital (education)*, refers to an emerging approach to learning mediated by various technological methods (Siemens, Gašević, and Dawson, 2015). Digital learning brings online, distance and blended learning under a single concept, and could be structured as formal/informal, self-regulated, structured/unstructured, or lifelong.

## Research Questions

The present study identifies student engagement metrics and contextual factors commonly used to model learning and predict learning outcome or course persistence in non-formal, digital educational settings. First, we examine traces of student activity operationalized as indicative of learning processes through a systematic review of the literature. We then use findings from the review to refine a well-established model of student engagement in the context of learning with MOOCs. Finally, we summarize the common methods used to examine the association between the metrics calculated and outcome measured, as means for defining and interpreting eventual association between different elements of the model constructs. To address these aims we posed the following research questions:

**RQ1.** What are the most common approaches to operationally defining and measuring learning outcomes? Is there misalignment between them with a common model of student engagement?

**RQ2.** What are the most common approaches to operationally defining and measuring learning context and student engagement? Is there misalignment between them with a common model of student engagement?

**RQ3.** What are the common approaches to studying the association between the identified metrics and measured outcome?

In contending that the majority of the current MOOC studies focus on the examination of the association between student engagement and course outcomes, Reich (2015) argues that “[d]istinguishing between engagement and learning is particularly crucial in voluntary online learning settings” (p.34, *ibid.*). However, Reich’s argument is limited to assessment scores, rather than on the individual and group changes that take place during and over the process of learning. According to Reich, introducing assessment at multiple time points, relying on the assessment methods validated in prior research, and making a better integration of assessment in the course design in general, are important steps in understanding learning in MOOCs (Reich, 2015). In part, we concur with Reich’s (2015) premise. However, we also acknowledge that not all MOOCs include (formal) assessment practices, especially those MOOCs designed with connectivist pedagogies (Siemens, 2005). Additionally, the diversity of student intentions for enrolling in voluntary online learning requires additional considerations on how learning might be operationalized in the context of MOOCs in the absence of assessment models. Moreover, Gašević, Dawson, Rogers, and Gašević (2016) stressed the importance of considering contextual factor when trying to predict learning outcome or course persistence. Framing their research around the Winne and Hadwin (1998) model of self-regulated learning, Gašević and colleagues (2016) showed how instructional conditions, as a vital component of external conditions affect the interpretation of learning-related measures. Therefore, we rely on the Reschly and Christenson (2012) model that observes student engagement as a mediator between contextual factors (e.g., intents) and learning outcomes, regardless of their operationalization. The model offers a broader view on the outcomes of learning, defining engagement as both a process and an outcome (Reschly & Christenson, 2012).

## **Method**

### **Literature Search and Inclusion Criteria**

To derive the extant research literature a computer-based search from 2012 to 2015 (inclusive) was undertaken over three phases (Figure 1). Although the first MOOC was offered in 2008, it was only in 2012 when the major MOOC providers (i.e., Coursera, edX and Udacity) were established, and an

inaugural course was launched<sup>1</sup>. Moreover, as noted by Raffaghelli, Cucchiara, and Persico (2015), it was only post 2012 when the MOOC research proliferated, demonstrating a growing maturation of the field.

The first phase involved a search of the following databases: EdiTlib, EBSCOhost (Education Source, ERIC, PsychINFO, PsychArticles, and Academic Search Complete), Scopus, Web of Science, Science Direct, Taylor & Francis, and Willey. The following search criteria were used for defining inclusion in the study:

Title, abstract, and/or keywords must contain at least one of the following terms:

*mooc\** **OR** *“massiv\* open online”* **AND**

Title, abstract, and/or keywords must contain at least one of the following terms:

*predict* **OR** *learn\** **OR** *associat\** **OR** *assess\** **AND**

Title, abstract, and/or keywords must contain at least one of the following terms:

*engage\** **OR** *outcome\** **OR** *retention* **OR** *interact\** **OR** *behavi\** **OR** *attrition* **OR**  
*dropout* **OR** *particip\** **OR** *complet\**.

The initial search resulted in 1,004 studies. After completing the search, two researchers coded the studies according to the inclusion criteria. The coding process comprised reading the title and abstract for each study and assigning a binary category – relevant/not-relevant. In cases where it was not obvious from the title and abstract whether a given study would be relevant for answering our research questions, the coders examined the article in detail (i.e., reading the methods and results sections). The coding was conducted through several steps. The first step included the joint coding of an initial set of 50 studies, in order to refine the inclusion criteria and to define a set of rules for accepting studies for the review. The changes between the original inclusion and exclusion criteria were minor. Specifically, the initial version of the inclusion criteria did not consider employees (e.g., we were not aware of the significant number of studies focusing on professional medical education), as it was further added to item (6) in the list below. Also, in the initial inclusion criteria, we had not been precise about item (8) from the list below, i.e., exclusion of studies relying on log data and surveys or questionnaires. These were later included as a special sub-set because they contained various learning-related metrics extracted from log-data, often used to describe the datasets of the analyzed studies. In other words, although such studies did not attempt to predict learning outcome of course persistence, they included operationalizations of learning-related constructs.

Two coders coded all the studies together and inter-rater agreement (Cohen, 1960) was calculated after coding 250, and 500 studies, as well as at the end of the coding process. All conflicts were resolved

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<sup>1</sup> <http://news.mit.edu/2012/edx-faq-050212>

at each of the steps. The two coders reached an average inter-rater agreement of 93.6%, with an average Kappa of 0.67. The final set included 96 studies that satisfied the following criteria for inclusion in this review, where the study:

- (1) presents an original (primary) research, analyzing MOOC data,
- (2) addresses a problem of predicting learning and/or persistence in MOOCs,
- (3) analyzed higher or adult education,
- (4) was published in 2012 or beyond,
- (5) was published in peer-reviewed journal/conference proceedings, available in English,
- (6) participants in primary studies were non-disabled undergraduate students, graduate students, and/or employees (e.g., teachers and nurses),
- (7) focuses on algorithms that help to identify variables related to learning,
- (8) relies on a log data and/or surveys/questionnaires, and the study applies inferential statistics and not primarily descriptive analysis to investigate the data.

Inclusion of both journal and conference papers in our systematic review was necessary. The exclusion of conference papers (and conference proceedings in computer science) would significantly limit the number of studies analyzed. In addition, the analysis targeted studies publicized at the onset of MOOC research, and publishing in conference proceedings would represent the most prominent way for disseminating novel research in a field. Their exclusion would also mean that research published in the main outlet for publication by computer scientist (for whom conference publications are mostly more important than journals), an important constituent group in the field, would be ignored. By integrating the literature from a variety of sources, this review aimed at summarizing the broadest possible set of learning-related metrics used to date. Such a broad overview did not negatively impact on the quality of the analysis. Rather, the extension of the review materials offered a fuller representation of the quantitative measures used to investigate learning at scale.

To ensure a comprehensive and accurate search was undertaken we manually searched the following journals: Journal of Learning Analytics, Journal of Educational Data Mining, British Journal of Educational Technology, The Internet and Higher Education, Journal of Computer Assisted Learning, The International Review of Research in Open and Distributed Learning, Journal of Educational Technology & Society, Educational Technology Research and Development, IEEE Transactions on Learning Technologies, Distance Education, International Journal of Computer-Supported Collaborative Learning, ACM Transactions on Computer-Human Interaction, and the International Journal of Artificial Intelligence in Education. A manual search was also conducted for conference proceedings including: International Conference on Learning Analytics and Knowledge, International Conference on Educational Data Mining, International Conference on Computer Supported

Collaborative Learning, ACM Annual Conference on Learning at Scale, ACM SIGCHI Conference on Human Factors in Computing Systems, ACM Conference on Computer Supported Collaborative Work, European Conference on Technology Enhanced Learning, and International Conference on Artificial Intelligence in Education Conference. The list of relevant journals and conferences was obtained from Google Scholar metrics list of top publications in the educational technology research category. The manual search resulted in an additional 23 studies, providing a total list of 119 studies selected for further consideration.

In the final phase, we coded the selected 119 studies according to the coding scheme (Appendix A). The coding scheme was developed with respect to the STROBE Statement<sup>2</sup> recommendations for the observational studies, adapted and extended to account for the specific research questions of this systematic review. Although the STROBE list has been primarily used in medical research, these recommendations for the observational studies are comprehensive, offering a valid basis for coding schemes used in other domains (such as educational research). Nevertheless, given the focus of our study, we removed items such as “Give reasons for non-participation at each stage”, as one of the aspects of describing study participants available in the STROBE recommendations, as well as “Funding” (also available among the STROBE items), as these items were not relevant for the context of the present study. Following the final screening by four independent coders 38 studies were identified that met the above-defined criteria for inclusion (Figure 1).

## Analysis

To address research questions, a synthesis of the 38 systematically selected studies was undertaken. The main focus of the systematic review was on the metrics used to assess learning in MOOCs and the outcome variables measured. Thus, each of the studies was coded with respect to these parameters. Moreover, we examined how different studies defined outcome (e.g., learning outcome or dropout), as well as how each of the predictors was extracted. Besides the variables used, we also indicated the statistical methods used to examine the association between predictors and outcome(s), and the noted results (if reported) for each of the analyses applied in the reviewed studies. A definition for each of the coded attributes is provided in Table S1 (please see supplementary material).

Additionally, the studies were coded with respect to (1) the theories they adopted to analyze learning (e.g., online or distance education theories) and (2) study objectives (e.g., predicting final course grade, or predicting drop-out). We also examined whether a study was exploratory or confirmatory, whether authors discussed limitations and generalizability of study findings, and to what extent pedagogical

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<sup>2</sup> <http://www.strobe-statement.org/index.php?id=strobe-home>

and/or contextual factors were considered. The main study findings across the reviewed literature were summarized to identify common and significant conclusions.

To contextualize the variables, and for further research, we coded the platform where a MOOC was delivered, the educational level suggested for each of the offered courses, course domain, and course completion rates. Due to numerous interpretations of how course completions are calculated (see Section 4.1), here we captured the count of registered, active students, and the number of students who obtained a certificate, if reported. Furthermore, we were interested in the domain of the analyzed courses. That is, whether the courses offered a certificate, and how many xMOOCs or cMOOCs were included in the analyses. The types of MOOCs were labelled based on the categorization commonly found in the literature distinguishing between the connectivist cMOOCs and Coursera-like xMOOCs (Rodriguez, 2012).

We also identified the data sources used for each of the studies included in the review as well as the study focus (e.g., all students, only students who posted to a discussion forum, or students who successfully completed a course).

## **Limitations**

The diversity of terms describing similar concepts and measures presented a significant challenge for this study. Researchers would frequently state that the study examined an association between “learning outcome” and various metrics of student engagement, without a clear description what was considered as an outcome. The lack of specificity in the reviewed studies prompted the need for added interpretations based on a review of the analyzed data. Additional challenges again related to a lack of detail surrounding the metrics used to measure variables associated with any developed predictive model. For example, simply stating that a measure included a “count of discussion activities” is insufficient detail. Simply referring to a broad count of activity does not make it clear if the metric included an aggregation of all possible discussion activities (e.g., posting, viewing, voting) or a specific subset.

The ability to determine measures of time-on-task also presents issues for the review. As Authors (2015c) pointed out, it is important to specify how time-on-task is determined and which (if any) heuristics or approximations were applied. This was not always the case with the studies included in this review. Therefore, the majority of the reviewed studies required detailed investigation of the methods applied and the description of the data analyzed to determine appropriate categorization. The lack of consistency in terminology necessitated further interpretations. Furthermore, we classified variables across the various dimensions of student engagement in light of Reschly and Christenson’s model. This classification added a level of subjectivity, which could lead to challenges in ensuring

internal validity. Finally, to maintain a quantitative focus, this study excluded often rich observations drawn from qualitative studies which would be more appropriate for a separate literature review.

### **Quantitative overview of the selected studies**

The aim of this section is to present the selected dataset of MOOC research papers. Specifically, here we reviewed 38 studies in relation to their bibliographic information and their overall focus prior to the in-depth analysis of learning-related metrics used in these academic papers.

Table 2 shows the author(s), titles, publication year, publication venue types, the number of courses analyzed, data sources used, and the number of students<sup>3</sup> (registered, active, completed) in the studies included in this review. We observed that, as noted in Figure 2, a majority of studies included in the systematic review were published at conferences (Figure 2). Although we reviewed the literature published between 2012 and 2015, only one study published prior 2014 satisfied the inclusion criteria.

Courses delivered on the Coursera platform were most commonly analyzed, followed by the edX platform (Figure 3). We observed that only a few studies examined courses delivered by other MOOC providers. For example, only one study analyzed data delivered via the D2L learning management system (Goldberg et al., 2015), Sakai (Heutte, Kaplan, Fenouillet, Caron, & Rosselle, 2014), UNED-COMA platform (Santos, Klerkx, Duval, Gago, & Rodríguez, 2014), or a course delivered in a distributed environment (i.e., Distributed), using social media (Authors, 2015a). Finally, only Adamopoulos's (2013) study utilized data from MOOCs delivered across various platforms (i.e., Canvas Network, Codecademy, Coursera, edX, Udacity, and Venture Lab). However, this study was not included in the summary provided in Figure 3, as it was not clear which of the 133 courses analyzed was delivered within the various platforms.

Most of the evidence derived from the modeling of learning behavior in MOOCs was collected from computer science courses (Figure 3). Physical science and engineering, life and social sciences, and arts and humanities courses were also well-represented. In contrast, language learning and personal development courses were rarely examined. This observation is reflective of the sheer volume of MOOC offerings related to the computer sciences compared to other disciplines (Shah, 2015), as well as the technical skills that are required to process MOOC data for analysis.

Only two studies within the dataset analyzed data from connectivist learning environments (Figure 3). Heutte et al. (2014) and Authors (2015a) incorporated data from social media (e.g., Twitter or blogs) in order to understand factors that could explain learning in cMOOCs. The remaining studies examined MOOCs that were designed in a more structured framework (i.e., xMOOCs).

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<sup>3</sup> Several studies did not report precise information about the number of participants included or did not report number of students at all, thus we noted “more than” a certain number of participants or noted as “NR”.



The systematic review further revealed that typically learning in MOOCs is studied through the analysis of the trace data combined with discussion or survey data, and is generally derived from a single course (Figure 4). Very few studies combined more than two data sources (e.g., survey, trace, and discussion forum data). Moreover, there was only one study that relied on learner-generated data., such as blogs, Twitter, and/or Facebook posts. On the other hand, studies that analyzed two or more courses primarily focused on trace or discussion forum data.

For most the courses analyzed, researchers reported 25,000 to 50,000 registered students (Figure 5). This size of cohorts is not surprising given that an enrollment of 25,000 students is commonly referred to as a typical MOOC size (Jordan, 2015b). However, the number of active students or students included in the analyses was generally less than 10,000. As indicated in Table 2, researchers often failed to report the number of registered and active/observed students in their studies.

## **Results and Discussion**

### **Common Operationalization of Learning Outcomes (RQ1)**

As a part of the first research question, our analysis aimed to identify how the reviewed literature defined the results of the learning process, and to discuss their alignment with a common model of student engagement. Specifically, we analyzed how researchers operationalized and measured the outcome variables they were predicting in their various models. Our analysis suggests that learning outcomes have been defined as course completion (e.g., Crossley et al., 2015; Loya, Gopal, Shukla, Jermann, & Tormey, 2015); engagement (Sharma, Jermann, & Dillenbourg, 2015), social interactions (Vu, Pattison, & Robins, 2015); sociability (Brooks, Stalburg, Dillahun, & Robert, 2015), and learning gains (Koedinger, Kim, Jia, McLaughlin, & Bier, 2015; X. Wang, Yang, Wen, Koedinger, & Rosé, 2015). The majority of studies use the metrics capturing in-course academic performance and persistence interchangeably with the notions of failure and success within the course (e.g., Adamopoulos, 2013; Santos et al., 2014; Sharma et al., 2015).

**Academic performance.** Academic achievement in the form of final exam or an accumulated course grade was the predominant variable or proxy for course outcome (Bergner, Kerr, & Pritchard, 2015; Coffrin, Corrin, de Barba, & Kennedy, 2014; Crossley et al., 2015; Gillani & Eynon, 2014; Kennedy, Coffrin, de Barba, & Corrin, 2015; Koedinger et al., 2015; Ramesh, Goldwasser, Huang, Daume, & Getoor, 2014b; Sinha & Cassell, 2015; Tucker, Pursel, & Divinsky, 2014; X. Wang et al., 2015). Alternative to the final grade, a course outcome was defined through basic levels of certification: e.g. ‘no certificate’, ‘normal certificate’ and ‘certificate with distinction’ (e.g., Brooks, Thompson, & Teasley, 2015); potentially complemented with additional categories such as ‘completing some exams’ and ‘completing all exams without passing the course’ (Engle, Mankoff, & Carbrey, 2015). In most

cases, these levels were derived from the grades, with the exception of Adamopoulos (2013) who asked students to self-report their level of performance from a predefined list.

**Cognitive Change.** Instead of using grades or categories representing performance to measure the result of learning, several studies employed measures to capture cognitive change of a learner. Champaign et al. (2014) defined course outcome as the improvement of students' ability to succeed on quizzes, i.e., if they were over-performing their prior grades, rather than whether they were receiving high scores. Konstan, Walker, Brooks, Brown, and Ekstrand (2015) took a somewhat similar approach by measuring the change in knowledge through 20-item pre- and post-class knowledge tests created by the instructor. Finally, Li, Kidziński, Jermann, and Dillenbourg (2015) conducted a study predicting the difficulty of the course content, that in a way reflected that if a learning material required more effort from a learner. Their study established an association between student viewing patterns of the in-course video lectures with student perceived video difficulty.

**Persistence and Drop-Out.** In our review, the studies predicting learning persistence were observed as another approach mainstream to the analysis of learning in MOOCs. Researchers appeared to willingly include course completion or course grade as a point of reference in persistent behavior. Many authors explicitly defined persistence as engagement with both content and assessment and sometimes forum activity as well. For instance, Ye and colleagues (2015) defined a drop-out as a learner who accessed fewer than 10% of the lectures and performed no further assessment activities. Vu and colleagues (2015) integrated participation in more activities than just assessment by operationalizing drop-out events as a stop of engagement in learning events spanning across the course activity including the forums as well as quiz grades. Alternatively, the students not earning a certificate and taking no action between a certain point in time and the time of the issuance of the certificates were defined as 'stop-outs' in the study by Whitehill, Williams, Lopez, Coleman, and Reich (2015). In some of the reviewed articles (e.g., Boyer & Veeramachaneni, 2015), the authors did not explain which learner activity was included as a measure of persistence from one week to the next, i.e., a task and/or a lecture.

In sum, we observed that persistent undertaking of assessment was commonly included as a full or partial indicator of how persistence was measured. Such can be interpreted as an indication of a limited understanding of MOOCs. That is, by defining persistence as a learning outcome and a predictor of interest, researchers indicate that the mindset guiding such analysis is similar to that applied in a university setting. Specifically, learners undertake courses where their learning is marked by assessments. However, MOOCs nature of open participation does not limit student learning to undertaking assessment, but is varied depending on students' motivation (Eynon, 2014). In a way, using persistence as a proxy for learning ignores the non-formal nature of MOOCs where students are not required to get assessed or follow through the course. For some of the individuals, learning happens

outside of continuous in-course assessment if they are sampling content or getting their ‘just-in-time’ insights relevant to a very specific question they are solving. Currently, these MOOC-specific groups with divergent intentions to learn that reach beyond the formal assessment and prescribed course activities are often grouped within an all-encompassing ‘no certificate’ category, the one dichotomous to full course completion.

In the analyzed dataset, the study by Sharma et al. (2015) was representative of academic work trying to work around pre-existing formal education assumptions about measuring the outcomes of learning through grades or continuous assessment. The authors expanded course outcomes to include learners who may not be pursuing certification. Measured outcomes were defined by either grades or degrees of interaction with the course material. The authors analyzed the association of clickstream data and performance with two main learner types clearly distinct in their desired course outcomes: active student (submitting graded assignments successfully, or failing) and a viewer (engaging in lectures and/or quizzes without graded assignments).

**Social and Affective Aspects of Learning as a Part of Learning Outcome.** A focus on social dimensions of learning outcomes was scarce as compared to academic performance or persistence. The majority of studies in this domain focused on the volume of posts or number of connections gained in course forums. Importantly, where social aspects of learning captured through the numbers of connections or posts were used as measured outcomes, they were included as complementary to grades. The number of forum posts is the most common measure of learning associated with the social interaction. This measure has been typically recorded at the end of the course (Brooks, Stalburg, et al., 2015; Goldberg et al., 2015). Alternatively, Authors (2015a) relied on the concept of social capital to explain the outcome of the learning process. Authors (2015a) used social network analysis to quantify individual positions in networks of learners. Authors (2015a) demonstrated that socially engaged MOOC takers with higher grades and socially engaged participants with higher social capital were not necessarily the same individuals. Such a result supports the premise that MOOCs are used differently by learners, and learning with others is only relevant to some individuals. In relation to students’ persistence in participating in MOOC forums, a series of studies focused on student disengagement from posting activity (X. Wang et al., 2015; Yang, Wen, Howley, Kraut, & Rose, 2015). Specifically, Wang and colleagues (2015), as well as Yang and colleagues (2015), found the relationship between the time students joined a MOOC and student difficulty in engaging with others in online discussion forums. This work emphasized the importance of the temporal aspect for modelling aspects of social interaction and collaboration (i.e., learning through the interactions with the others) as an outcome.

Affective aspects of learning outcomes were rarely incorporated into the learning outcomes and were limited to student satisfaction.

**Multi-dimensional measures.** Some authors used multi-dimensional measures of course outcomes. For instance, Kizilcec and Schneider (2015) predicted learner behavior that was operationalized as a multidimensional construct. The authors approached learning behavior as defined by learner progress in the course, their general performance, and social engagement. The dimension of learner progress was quantified by the proportion of watched videos and attached assignments (more than 10%, more than 50%, and more than 80%). General performance was operationalized as receiving a certificate of completion. Finally, social engagement was operationalized through a combination of the number of posts (in relation to the most prolific learner) and received votes. Again, although the focus on metrics typical in formal courses is evident, the authors integrated different dimensions that described the learning outcomes.

Overall, in analyzing measured outcomes of learning in the selected studies we observed formal education mindset guiding researchers using measures related to certification, assessment and prediction of drop-out as undesired behavior. Such is not surprising, as the literature stemming from formal educational contexts has validated measures allowing to capture learning as performance, or learning as progress towards completion, or learning as participating in assessment. Hence, operationalizing the learning outcome perceived through an academic (formal education) lens is mostly developed. Few authors maintained focus on measuring cognitive change; whereas the focus on social outcomes of learning is scarce, with the emphasis on the volume of posts or number of connections. Affective aspects of learning outcomes are currently limited to student satisfaction. Few studies employed a more holistic approach using multi-dimensional constructs to measure (and predict) learning outcomes, or by distinguishing that not all learners in MOOCs can be described by a more common university-like profile.

In their model of engagement Reschly and Christenson (2012) described learning outcomes of two broad types. The so-called proximal learning outcomes indicate the product of the learning process that can be proximal and distal. According to the authors, proximal learning outcomes can fall under academic, social and emotional sub-categories (Figure S1 – please refer to the supplementary material). A proximal learning outcome is used to indicate school-related outcomes, such as grades, relationships with peers, self-awareness of feelings, among others. Distal learning outcomes are observed in post-graduation settings related to adult life. In the model, these are exemplified as for instance related to employment or productive citizenry. Such distinction between what is learnt and applied at school and what is learnt and beyond is fitting in a K12 setting for which the authors developed their model. The MOOC context, however, has some differences. For the majority of their participants, MOOC experiences do not aggregate to ten years of relationships within a community where formal assessment is necessary at different phases. The MOOC participants may be interested in a timely content they

need to learn as they engage for a short period of time. Alternatively, they also may undertake the MOOC in its entirety and follow all different learning goals set throughout the entire offering. Therefore, we suggest that proximal learning outcomes are redefined into the immediate and course-level, instead of the school-level, otherwise preserving their academic, social and affective aspects. For the distal learning outcomes, we suggest to redefine them as post-course, instead of referring to them as distal learning outcomes. These suggested modifications are captured in Figure 6 demonstrating the re-operationalized model, whereas the table that summarizes all the studies included in the review along with the learning outcome measured is provided in the supplementary material (Table S2).

## **Providing means for defining context and engagement types in learning at scale**

### **(RQ2)**

A challenge for this systematic review involved summarizing a wide variety of variables used to model learning in MOOCs. This was particularly noted in the definition of latent constructs various studies claim to measure. Thus, for example, several studies measured engagement as a latent construct (Ramesh, Goldwasser, Huang, Daume, & Getoor, 2014a; Ramesh et al., 2014b; Santos et al., 2014; Sinha & Cassell, 2015). However, Santos et al. (2014) focused primarily on metrics extracted from students' interaction within a discussion forum. Ramesh and colleagues (2014a, 2014b), as well as, Sinha and Cassell (2015) also considered students' interaction with other course resources (e.g., quizzes, videos, or lectures). On the other hand, Wang et al. (2015) measured discussion behavior operationalized through the cognitive activities extracted from discussion forum messages. Nevertheless, most studies, although focusing on somewhat similar or same metrics, did not report constructs measured. That is, those researchers focused on the measures of student activity with the course materials or with their peers (e.g., counts of videos watched, number of messages posted), without necessarily defining such measures as engagement. Although some of the studies used the same operationalization of the measured variable, those metrics were usually labeled in different ways (e.g., discussion behavior, behavior, or engagement). Therefore, in order to provide a more coherent summary of findings, we framed our results around the constructs introduced in Reschly and Christenson's (2012) model of student engagement and adopted in our study (Figure 6).

**Contextual variables.** A significant number of studies (39.5%) included in the systematic review, observed contextual variables in order to determine to what extent student demographic data (10 studies), course characteristics (5 studies), or student motivation (8 studies) predict learning outcome and/or course persistence. Only one study (i.e., Konstan et al., 2015) observed all three contextual factors. On the other hand, a majority of studies that analyzed demographic data (around 66%) also observed either motivational factors or course-related characteristics.

Demographic variables have been commonly used in understanding factors that influence learning in MOOCs. Age, gender, and level of education were considered in various studies in terms of predicting course persistence and/or achievement. Some 80% of studies that observed demographic data (i.e., out of 15 studies) included the level of education of course participants. The results somewhat differ across the studies included in the review. Goldberg and colleagues (2015), as well as, Heutte and colleagues (2014) found no significant difference in a likelihood of completing a course across the observed levels of education. The studies observed rather different course settings – health and medicine xMOOC delivered on the Desire2Learn platform Goldberg et al. (2015), and a distributed (cMOOC) version of a humanities course (Heutte et al., 2014). Moreover, Konstan et al. (2015) found no significant association between the level of education and knowledge gain or a final course grade, in a data science xMOOC, delivered using the Coursera platform. However, through the analysis of courses from various disciplines delivered on the Coursera platform, Engle et al., (2015) Greene, Oswald, and Pomerantz (2015), Kizilcec and Halawa (2015), and Koedinger et al. (2015) showed that more educated students are more likely to persist in a course and achieve higher grades.

Existing research does not provide univocal conclusions with respect to the importance of **students' age** for predicting course persistence and achievement. Engle et al. (2015), Koedinger et al. (2015), and Konstan et al. (2015) failed to find an association between students' age and course completion, final course grade, or knowledge gain. Whereas, on the other hand, Greene et al. (2015), Heutte et al. (2014), and Kizilcec and Halawa (2015), showed that older students were more likely to persist with a course. However, Kizilcec and Halawa (2015) also showed that older students achieved lower grades compared to their younger peers.

The prevailing understanding found in the studies included in this systematic review that observed students' **gender** (5 studies) as an important determinant of learning in MOOCs, is that there are no differences between male and female students with respect to the course persistence, course outcome, and attained knowledge gains (Adamopoulos, 2013; Heutte et al., 2014; Koedinger et al., 2015; Konstan et al., 2015). Only Kizilcec and Halawa (2015) showed that male students were more likely to persist with lectures and assessment, as well as to achieve a grade above 60<sup>th</sup> percentile, across a wide range of courses (i.e., 21 courses) from various subject domains.

The existing literature on student motivation and engagement in online learning argue that the lack of student affinity to complete a course leads to higher dropout rates, and consequently failure to complete a course (Hartnett, George, & Dron, 2011). Thus, intention to complete a course and number of hours intended to devote to a course work, are commonly considered in predicting course persistence and achievement (i.e., included in 40-50% of studies that observed student motivation). Except for Konstan et al. (2015), who failed to confirm the association between students' intention (i.e., complete

a course, and time devoted) and final course grade, findings from other studies (i.e., Engle et al., 2015, Greene et al., 2015, Heutte et al., 2014, and Kizilcec and Halawa, 2015) confirmed general understanding of students' **intrinsic motivation** for persistence and achievement in MOOCs.

Generalizing the findings with respect to the **course** (or **classroom**) characteristics is rather challenging given a diverse set of metrics used in the studies included in this systematic review. For example, Adamopoulos (2013) showed a negative effect of course difficulty, planned workload, and course duration (in weeks) on student retention. It is also interesting that Adamopoulos's (2013) study revealed a negative effect of self-paced courses, compared to more structured course design on successful course completion. On the other hand, Adamopoulos (2013) also showed that peer assessment (compared to automated feedback), and open textbooks, had positive effects on successful course completion. Likewise, Konstan et al. (2015) showed that being in a specific course track (i.e., programming vs. concepts track<sup>4</sup>) significantly predicts course grade, also being negatively associated with normalized knowledge gains. Finally, Brooks and colleagues (2015) revealed that the fact whether students were paying for a certificate or not, had a minimal predictive power on course grades.

Although original Reschly and Christenson's model (Figure S1) argues for the importance of understanding context through the four factors, namely *family* (e.g., support for learning, goals and expectations), *peers* (e.g., educational expectations, shared common values, aspiration for learning), *school* (e.g., instruction and curriculum, support, management), and *community* (e.g., service learning), contemporary MOOC research suggests somewhat different operationalization of the contextual elements. Therefore, for research of learning at scale we argue that contextual factors should be observed through students' *demographic* data (e.g., age, gender, level of education), *classroom* characteristics (e.g., peers, course characteristics, course platform), and *individual* students' *needs* and motivation (e.g., intent to complete a course, interests in topic), as outlined in Figure 6. It should be noted here that "classroom characteristics" primarily refer to the specific attributes of the given course and not to the notion of the traditional (i.e., face-to-face) classroom.

**Student Engagement.** Given the purpose of the systematic review and specified search criteria, unsurprisingly, 89.5% of the studies went beyond contextual factors (primarily demographic data) and included engagement-related metrics in predicting retention or achievement in MOOCs. A considerably smaller number of studies (21%), however, attempted to align extracted metrics with existing educational variables. Such an approach resulted in a wide diversity of variables used to quantify student engagement in non-formal, digital educational settings.

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<sup>4</sup> The course design in Konstan, Walker, Brooks, Brown, and Ekstrand (2015) study included two tracks: 1) programming track that included assignments and all the content, and 2) concepts track that was focused on learning programming concepts, without programming assignments and with only few video lectures related to specific programming tasks.

Around 20% of the studies included in the review is the total number of messages students contributed in a discussion forum, during a course. Crossley and colleagues (2015), Engle and colleagues (2015), Goldberg and colleagues (2015), as well as, Vu and colleagues (2015), showed that students who actively participated in the discussion forum (i.e., created a high number of posts) were more likely to complete a course. However, predicting knowledge gain or exam score, yielded somewhat different results. Specifically, Konstan and colleagues (2015) showed that the number of messages posted to a discussion forum was not significantly associated with an increase in knowledge gain. Similar findings were noted by (X. Wang et al., 2015), who showed there was no association between forum participation and knowledge gain. Finally, Vu and colleagues (2015) also showed that the overall activity in discussion forums did not predict the number of quiz submissions nor submission scores. As explained by Vu and colleagues (2015), the relationship between the number of posts and assessment grade seemed to be one-directional. That is, higher grades predicted the number of posts, but the number of posts did not necessarily predict the grade.

A substantial number of studies that measured various forms of student engagement also observed to what extent interaction with course assessment (17.6%) (e.g., the number of total assignment submissions, count of correct quiz attempts) predicted learning outcome or retention. In general, studies showed a significant and positive association between assignment and/or quiz interaction and successful course completion (Brooks, Thompson, et al., 2015; Konstan et al., 2015; Sharma et al., 2015; Ye et al., 2015). Nevertheless, Kennedy and colleagues (2015) revealed somewhat contradictory results, failing to demonstrate the association between the number of submitted assignments and course performance (i.e., final course grade).

To evaluate the quality of student generated discourse and examine the association between student cognitive behavior and learning, researchers mainly relied on content analysis methods to identify underlying cognitive processes. For example, analyzing cognitively relevant behaviors in discussion forum messages using Chi's ICAP framework (Chi, 2009), Wang and colleagues (2015) showed that active and constructive cognitive processes could predict learning gains. On the other hand, Yang et al. (2015) demonstrated the importance of resolving confusion in the discussion forum in order to reduce student dropout. However, in detecting different confusion states, Yang and colleagues (2015) relied on psychologically meaningful categories of words, extracted from online discussions using the Linguistic Inquiry and Word Count (LIWC) tool (Tausczik & Pennebaker, 2010), as one of the classification features. Whereas, Authors (2015a), as well as Authors (2015b), exemplified how linguistic indices of text narrativity, cohesion and syntax simplicity extracted from online discussion transcripts predict learning outcome and social positioning in various contexts.



Similar to studying cognitive processes, researchers primarily relied on content analysis methods when studying affect in MOOCs, and the association between affect and course persistence or outcome. Thus, Tucker and colleagues (2014) revealed a strong negative correlation between student sentiment expressed in the discussion forum and average assignment grade. Whereas, this correlation was low and positive between student sentiment and quiz grades. Tucker and colleagues (2014) relied on a word-sentiment lexicon (Taboada, Brooke, Tofiloski, Voll, & Stede, 2011), and Adamopoulos (2013) used AlchemyAPI to extract student sentiment from discussion forum messages. Adamopoulos (2013) further showed that student sentiment towards course instructor, assignments, and course materials have a positive effect on the course retention. Yang and colleagues (2015) on the other hand, highlighted the importance of resolving confusion (expressed in student forum posts) in order to increase retention. However, in order to detect confusion from student contribution to the discussion forum, Yang and colleagues (2015) relied on LIWC features (among others) and word categories that depict student affective processes, including positive and negative emotions.

Through the analysis of the results related to our second research question, we were able to observe a large diversity of metrics used to understand learning and predict student persistence and/or course outcome. Given a large scale and various sources of data, it seems that the first generation of MOOC research (Reich, 2015) primarily focused on understanding “what works” in this new settings, in terms of supporting learning activities and increasing retention. However, another reason for such diversity of metrics used (Table S3 – please refer to the supplementary material) presumably lies in the fact that there is no single commonly accepted analytical method or framework that would allow for studying learning in non-formal, digital educational settings. Failing to provide a common interpretation of observed variables used to understand learning can potentially lead towards limited generalization and low interpretability of results.

Table S3 (please refer to the supplementary material) provides a complete list of metrics, extracted from the studies included in this systematic review, used to model learning in non-formal learning settings. In the following text (Section 5 primarily), we also provided a rationale for conceptualizing learning in MOOCs and definition of the constructs that comprise the adopted model of the association between context, engagement, and proximal learning outcome.

Following the original Reschly and Christenson’s model, we argue that studying learning at scale should observe four engagement types – behavioral, academic, cognitive, and affective engagement (Figure 6). However, we propose different conceptualizations of each type of engagement in this context given the specific nature of learning with MOOCs and characteristics of data collected about students’ learning. Each of the engagement types and associated learning-related metrics that belong to

the four dimensions of engagement are discussed in more details in the section “Conceptualizing Learning in MOOCs”.

### **Association between metrics identified and measured outcome (RQ3)**

In addition to the reviewed inter-study variability in outcomes (Section 4.1) and predictors (Section 4.2) assessed, we also observed differences in statistical approaches to studying the association between engagement metrics and learning outcomes in MOOCs. Statistical approach refers to whether the models employed a correlational, ANOVA, regression, linear mixed-effects, survival analysis, social network analysis, or various machine learning techniques. Table 1 provides a summary of the commonly used statistical methods.

A majority (34.21%) of the included papers reported using a machine learning approach (e.g., classification using random forest or J48 algorithms), and correlation, chi-square test, regression, ANOVA or MANOVA, social network analysis (SNA), survival analysis, and mixed-effects regression were reported much less often. Five additional papers used statistical methods that occurred less than three times total and thus were classified as “other”. These statistical tests included t-test (n = 2), relational event modeling (n = 1), discrete choice model (i.e., random utility model or latent regression model; n = 1), or a structural equation model (SEM; n = 1).

A few insights can be gleaned from Table 1. The most common analysis method adopted was machine learning techniques. Of the papers that used machine learning approaches, only 38% of the 13 also reported another statistical method. The usage of machine learning suggests that a common goal among the papers was to build predictive models (versus explanatory models). Indeed, the goal of predicting students’ success in MOOCs is a highly relevant goal for incorporating interventions. It is also important to point out that correlational and regression techniques were also commonly used (36% combined). This may suggest that another important goal among these papers was to not only build predictive models but also explain variance in the dependent variable(s) of interest. Taken together, the statistical methods were quite diverse, perhaps targeting different theoretical or more applied goals.

### **Conceptualizing Learning in MOOCs**

This systematic review of the MOOC research literature involved two related aims. The first involved the development of a summary of the metrics that are commonly used to measure and model learning in non-formal educational settings. The second aim was to extend these findings and establish a conceptual model that would distinguish between the factors impacting students’ learning in a MOOC context. Building on Reschly and Christenson (2012) model of the associations between context, engagement, and student outcomes, we further redefined and re-operationalized these constructs (i.e., context, engagement, and outcome) for research on MOOCs. In so doing, we relied on the insights

obtained from the systematic literature review to understand how the diversity of learning-related constructs are measured in MOOCs, and how these constructs could be used to provide a connection with an existing model of learning that was previously validated in educational settings. One of the advantages of providing such a model lies in the possibility to compare factors of successful learning in non-formal, digital educational settings with more formal (e.g., traditional face-to-face or online) formats of learning. Specifically, such a model could provide a means for comparing whether, and to what extent, factors that contribute to learning differ across various educational contexts settings (e.g., face-to-face; online and MOOCs). Figure 6 presents the adapted model of the association between the context, engagement and learning outcome, with specific indicators characteristic for MOOC learning settings. The figure indicates a mediating role of student engagement in MOOCs, between contextual factors and desired learning outcome. Table S1 provides further operationalization for each of the constructs of the adopted model, based on the insights obtained from the systematic review.

In the context of MOOCs, our systematic review indicated a mainly exploratory nature of the existing research that attempts to investigate the association between various forms of student engagement (or behavior) and learning – defined through learning outcomes or course persistence. In so doing, researchers often failed to account adequately for existing educational frameworks that would allow for more salient interpretations of the results. Even when relying on existing learning theories, researchers generally do not account for a different learning context or a greater diversity of students observed in open non-formal educational context if compared to online or face-to-face settings.

Following the intention to provide coherence into the diverse analyses of learning-related constructs in MOOCs (Section 4), we framed our inquiry around Reschly and Christenson's (2012) work on dropout prevention and enhancing learning in traditional classroom settings. Showing that engagement drives learning and predicts learning outcome, Reschly and Christenson (2012) recognized student engagement as a two-fold construct – both a process and an outcome – that mediates the association between a context (e.g., student intentions, classroom settings) and a relevant learning outcome. Given that the majority of studies in this review, and in MOOC research in general according to Reich (2015), observe certain form(s) of students' engagement in predicting course outcome and/or persistence, it seems reasonable to provide a re-operationalization of this particular concept for a MOOC context.

Despite an extensive body of research on student engagement in various educational settings, and prevailing understanding of its importance, there is no clear consensus what comprises engagement (Christenson, Reschly, & Wylie, 2012). As noted in the Christenson et al. (2012) review, researchers most commonly refer to two subtypes (i.e., participatory and affective) or include a cognitive engagement as a third subtype. However, there are notable differences in how various subtypes of engagement have been operationalized in a traditional educational context. Thus, the lack of agreement

on how engagement has been defined and operationalized in MOOCs (see Section 4.2) perhaps comes as no surprise. Nevertheless, we posit that an attempt to establish a common understanding of how engagement is measured and interpreted in the context of learning in non-formal, digital educational settings is a necessary step towards better understanding learning in this particular context.

Although Reschly and Christenson (2012) observed engagement in traditional learning settings, the theoretical and practical stances considered in conceptualizing the engagement model, seem to align with the general understanding of what important factors of learning in MOOCs are. Specifically, a multidimensional nature of variables observed when assessing learning in non-formal educational settings (Table S1) supports the necessity to have multidimensional constructs that include different types of learner activity (e.g., Konstan et al., 2015; Sinha & Cassell, 2015), emotions (e.g., Crossley et al., 2015; Yang et al., 2015), or cognition (Dowell et al., 2015; X. Wang et al., 2015). Finally, similar to Kizilcec and Halawa (2015), Brooks and colleagues (2015), and Reschly and Christenson (2012) argue for the importance of considering a specific learning context (e.g., peers or school) and student agency. In spite of some similarities, operationalizing student agency in Reschly and Christenson's (2012) model is somewhat different from what has been considered in MOOC research included in this study. Reschly and Christenson (2012) draw on the assumption that “students are able to report accurately on their engagement and environments” (p.9, *ibid.*). Although we agree that “student perspective is essential for change in student learning and behavior” (Reschly & Christenson, 2012, p. 9), we further aim at extracting a majority of evidence of student engagement from the data stored within learning platforms used to deliver courses at scale.

Reschly & Christenson's model was designed to analyze formal educational settings. Thus, we further review the consistency of their model's categories in relation to the metrics observed in MOOC studies. First, we find that academic engagement in MOOCs aligns with Appleton, Christenson, Kim, and Reschly (2006) and Reschly and Christenson's (2012) work, and refers to time spent on course activities (e.g., viewing pages, engaging with quizzes and assignments), number of days (weeks, hours) being engaged with a course, assessment (e.g., homework, and quiz), completion rate and accuracy, credit towards course completion, and pre- and/or post-test results (e.g., Boyer & Veeramachaneni, 2015; Li et al., 2015).

Second, our view of behavioral engagement aligns with the original model of engagement (Reschly & Christenson, 2012). A common definition of behavioral engagement “draws on the idea of participation; it includes involvement in academic and social or extracurricular activities and is considered crucial for achieving positive academic outcomes and preventing dropping out” (Fredricks, Blumenfeld, & Paris, 2004, p. 60). For MOOCs, this form of engagement can still be defined through

participation in discussion forums, viewing lectures, following course activities, or number of times student accessed course wiki pages (e.g., Li et al., 2015; Santos et al., 2014; Sinha & Cassell, 2015).

Third, cognitive engagement usually refers to students' motivational goals and self-regulated learning skills (Christenson et al., 2012; Fredricks et al., 2004; Reschly & Christenson, 2012). In the context of learning with MOOCs, thus far research has primarily focused on linguistic indicators (e.g., text narrativity or cohesion) of student cognitive engagement, obtained from learner generated artefacts (Authors, 2015a; Authors, 2015b; X. Wang et al., 2015). The rationale behind this subtype of engagement is grounded in the premise that learning and understanding in computer-mediated learning are primarily expressed through the artefacts students generate in the learning process (Goodyear, 2002; Jones, 2008). Thus, studying learning in MOOCs should account for the quality of discourse, as a proxy for students' cognitive engagement.

Fourth, Reschly and Christenson's (2012) model of engagement considers students' affective reactions in the classroom, school identification, valuing learning, and sense of belonging as factors that characterize affective engagement. However, drawing on the premise that language represents a primary means of communication in computer-mediated interactions, as well as the lack of social cues that characterize learning in non-formal, digital educational settings, MOOC research primarily relies on linguistic indices in assessing affective engagement (e.g., positive or negative emotions) in MOOCs (e.g., Adamopoulos, 2013; Tucker et al., 2014). Nevertheless, there has been significant work done recently in assessing student emotions and affect using certain (arguably) more advanced approaches (e.g., Baker, D'Mello, Rodrigo, & Graesser, 2010; D'Mello, Dowell, & Graesser, 2009; D'Mello & Graesser, 2011).

Finally, failing to account for contextual determinants of learning in general (Appleton et al., 2006) or the contextual factors for online and distance education in particular (Gašević et al., 2016; Authors, 2016) could lead towards misinterpretations of the association between engagement and learning, providing an intervention that might not result with an intended outcome. In defining contextual variables, our understanding of factors that frame learning in MOOCs is defined through demographic data about course participants, classroom settings (e.g., peers and course design), and student individual needs (e.g., intent to complete and interest in topic) (Adamopoulos, 2013; Brooks, Stalburg, et al., 2015; Kizilcec & Halawa, 2015).

Course-level learning outcomes are the most commonly assessed in current MOOC research. They are also further developed as they reach beyond the focus on academic achievement, and include social and affective aspects. Thus, knowledge mastery as the outcome is measured through graded assessment. Alternative metrics are also employed, such as capturing knowledge or skill change. Course-level learning outcomes within the social aspect are limited to engagement with others, rather than the

measures of quality of the knowledge construction within the dialogue, or capture of the increased sense of belonging or identity formation. Affective course-level outcomes are limited to course satisfaction only. In contrast, Reschly and Christenson's model defined affective learning outcomes as self-awareness of feelings, emotional regulation, and conflict resolution skills.

Both intermediate and post-course outcomes are not of the main focus in current MOOC research. This is too constraining as such kinds of outcomes seem to be common in non-formal and open settings. For instance, intermediate learning outcomes are of relevance to the vast numbers of just-in-time learners sampling parts of the content. Current approaches to the identification of immediate learning outcomes in MOOC research is limited to academic performance, as the majority of metrics is focused on either predicting module outcomes, or detecting when a student stops engaging with the course. Reschly & Christenson's model, however, argues that engagement can be seen both as the process, as well as the outcome. Thus, it could be hypothesized that engagement metrics could serve as indicators of an intermediate learning outcome for those learners not interested in course completion.

When it comes to post-course outcomes, exemplified as employability and productive citizenry in the original model, they have not been the subject of much MOOC research, with the exception of the focus on employability (E. Y. Wang & Baker, 2015). Again, the lack of focus beyond assessment is limiting, as better measures of post-course outcomes could enrich stakeholders' understanding of the wider impact of MOOCs, and finally evaluate the value of producing MOOCs.

## **Conclusions**

MOOC research has demonstrated significant advances in a relatively short time frame (Raffaghelli et al., 2015; Reich, 2015). Nevertheless, contemporary research in MOOCs almost unequivocally argues for the lack of generalizability of existing results, and for failing to investigate factors that contribute to learning in non-formal, educational settings (DeBoer et al., 2014; Evans et al., 2016). To advance the field of research in non-formal, digital educational settings, there is an imperative to shift the focus from observational studies and introduce more experimental research approaches across different domains and course designs (Reich, 2015). Moreover, we agree with Reich's (2015) assumption that future MOOC research should build on the existing research frameworks, evaluated across educational contexts, in order to provide a basis for comparison between learning in MOOCs and other (more traditional) settings.

Our contribution to the development of the next generation research in non-formal, digital educational settings is twofold. First, we conducted a systematic literature review of the existing body of research in MOOCs that tries to model learning in this particular setting. We were able to identify a wide range of metrics used to predict learning and measure student engagement, across various contexts (e.g., centralized within a single platform, or distributed, using various social media). Nevertheless,

usually referred to as a *discussion behavior* (Wang et al., 2015), *behavior* (Ramesh et al., 2014a, Ramesh et al., 2014b), or *engagement* (Santos et al., 2014, Sinha and Cassell, 2015, Tucker et al., 2014), various researchers tended to observe engagement-related metrics from a single perspective operationalized through students' participation in different activities. Specifically, researchers tend to measure engagement as a form of participation in discussion forums (quantity of contribution) (Vu et al., 2015; X. Wang et al., 2015), watching video lectures (Li et al., 2015), or participating in course assessment activities (Whitehill et al., 2015; Ye et al., 2015). It is also noticeable that the definition of a course outcome is dominated by the formal education mindset for the majority of studies included in this review (Appleton et al., 2006). Regardless of the fact that various researchers have argued for the importance of aligning learning outcomes with students' intentions and interest in completing a course, only a few studies (e.g., Authors, 2015a; Authors, 2015b) made a considerable effort towards the operationalization of social or affective learning outcome (Figure 6).

The second part of our contribution is framed around the redefinition of the existing educational framework in order to account for specific aspects of learning in MOOCs. Specifically, following Reschly and Christenson's (2012) research, we proposed a model for studying the association between context, student engagement and learning outcome (Figure 6). We further suggest that engagement in MOOCs, and learning at scale in general, should be observed as a multi-dimensional construct, comprised of academic, behavioral, cognitive, and affective engagement. Such a definition should bring coherence into MOOC research, providing a common understanding what engagement actually is and how it should be measured in this complex learning context, which seems to lack in the existing studies. We also provided a list of metrics used to operationalize elements of the proposed model (Table S1). However, by no means, we argue that this is a complete list of metrics used to measure learning (or engagement) in MOOCs.

We contend that for advancing the MOOC research and allowing for comparisons with different (more traditional) forms of education, researchers should align metrics used for assessing learning with the proposed model. Having a generally accepted conceptualization of engagement would allow for obtaining more comprehensive insights into the factors that influence learning with MOOCs as well as how these factors could be generalized across different platforms or compared with diverse context (such as traditional online or face to face learning) (DeBoer et al., 2014). Such a conceptualization would also allow for moving beyond observing student "click data" and exploring how quantity and quality of interactions with the course content, peers, and teaching staff could predict course outcome and persistence, thus providing more salient connection with existing learning theories and practices (Dawson, Mirriahi, & Gasevic, 2015; Gašević et al., 2016; Wise & Shaffer, 2015). Nevertheless, we also acknowledge the lack of metrics in some aspects of the model – i.e., social and affective learning

outcomes – that require further conceptualization in the context of learning at scale. Recent advances in the (multimodal) learning analytics research field provide a promising venue for investigation of students' cognition, metacognition, emotion, and motivation using multimodal data, such as eye gaze behaviors, facial expressions of emotions, heart rate and electro-dermal activity, to name a few (Azevedo, 2015; D'Mello, Dieterle, & Duckworth, 2017; Molenaar & Chiu, 2015).

Our future research will examine the hypothesized association between context, student engagement and learning outcome. Thus, the proposed model (Figure 6) assumes a mediating effect of student engagement between contextual variables and desired outcome, which is in line with the original model proposed by Reschly and Christenson (2012). Reschly and Christenson (2012) also observed affective and cognitive engagement as mediating factors for the development of behavioral and academic engagement (as indicated with arrows from cognitive and affective to academic and behavioral engagement). However, given the proposed operationalization, this association may not hold in our proposed model. It seems reasonable to expect that direction of the mediating effect would be from behavioral towards cognitive and affective engagement. This assumption is simply due to the fact that in order to reveal traces of cognitive and affective engagement (as currently operationalized) students should first engage with course material and peer learners (i.e., reveal traces of behavioral engagement). Nevertheless, in order to examine those assumptions, we aim to create a statistical model(s) that would allow us to determine the validity of the hypothesized relations.

The original model, as proposed by Reschly and Christenson (2012), also assumes the *Matthew Effect* (Ceci & Papierno, 2005) between the contextual factors and engagement “wherein as students are engaged, contexts provide feedback and support that promote ever greater engagement” (Reschly & Christenson, 2012, p. 9), as indicated with the arrows pointing from context to engagement and vice versa). We posit that in the context of learning at scale, and MOOCs in particular, this association would still hold. Such an implication could be inferred from the existing research on self-regulated learning. Specifically, Winne and Hadwin (1998) model of self-regulated learning posits that *conditions* (i.e., learning experiences, domain knowledge, motivation, intents), operationalized here through the contextual variables, influence both “standards as well as the actual operations a person performs” (Greene & Azevedo, 2007, p. 336). Through *cognitive evaluation*, students compare *products* and *operations* (here operationalized through the four engagement types) to determine whether a learning goal has been achieved or further adjustments to the cognitive conditions should be applied, completing thus a recursive model of self-regulated learning (Greene & Azevedo, 2007; Winne & Hadwin, 1998).



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## Tables

TABLE 1

*OVERVIEW OF STATISTICAL APPROACHES REPORTED IN REVIEWED PUBLICATIONS*

Statistical approach	Number of studies used	Proportion of studies used
Machine learning	13	0.34
Descriptive	9	0.24
Correlational	7	0.18
Regression	7	0.18
Chi-square	7	0.18
MANOVA/ANOVA	6	0.16
Survival analysis	5	0.13
Linear-Mixed models	3	0.08
Other	5	0.13

## Figures

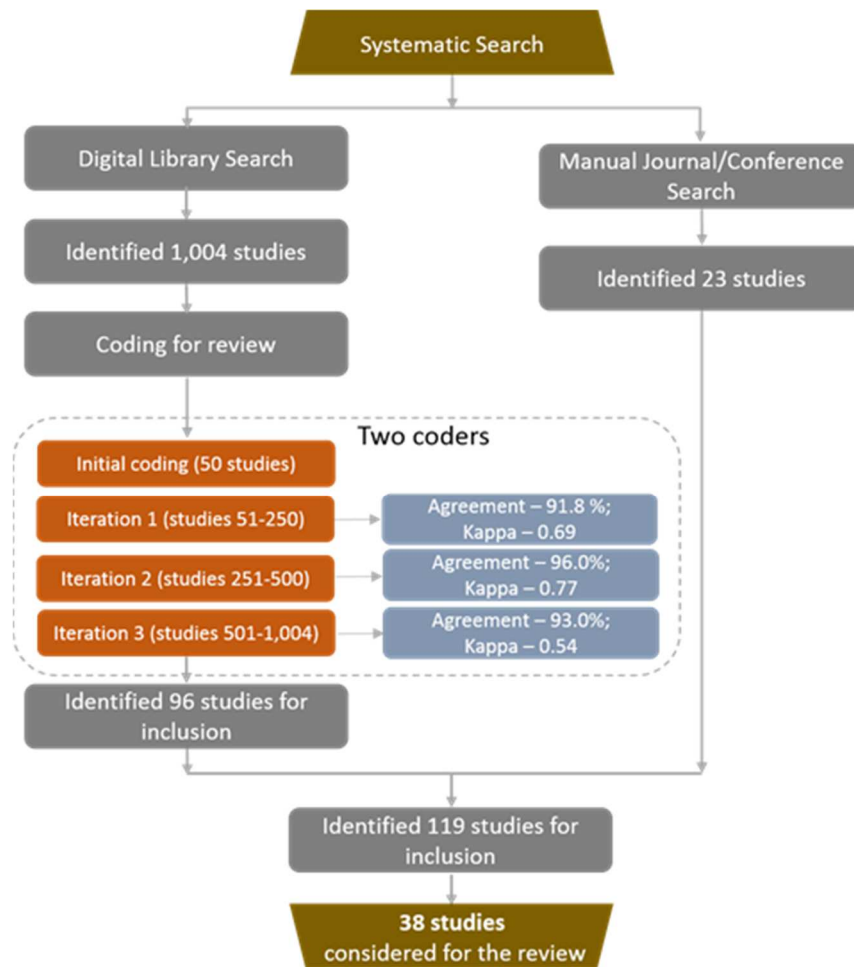


Figure 1. Overview of the systematic search and coding process

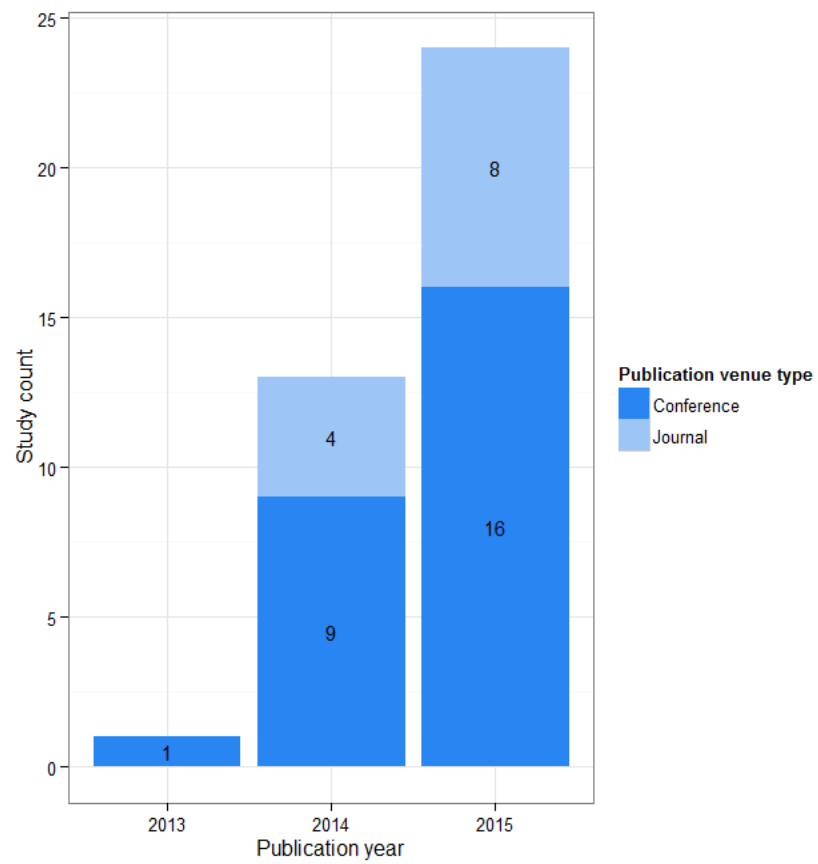


Figure 2. The number of studies per year, with bars showing the respective number of papers published in respective venues (i.e., journal or conference).

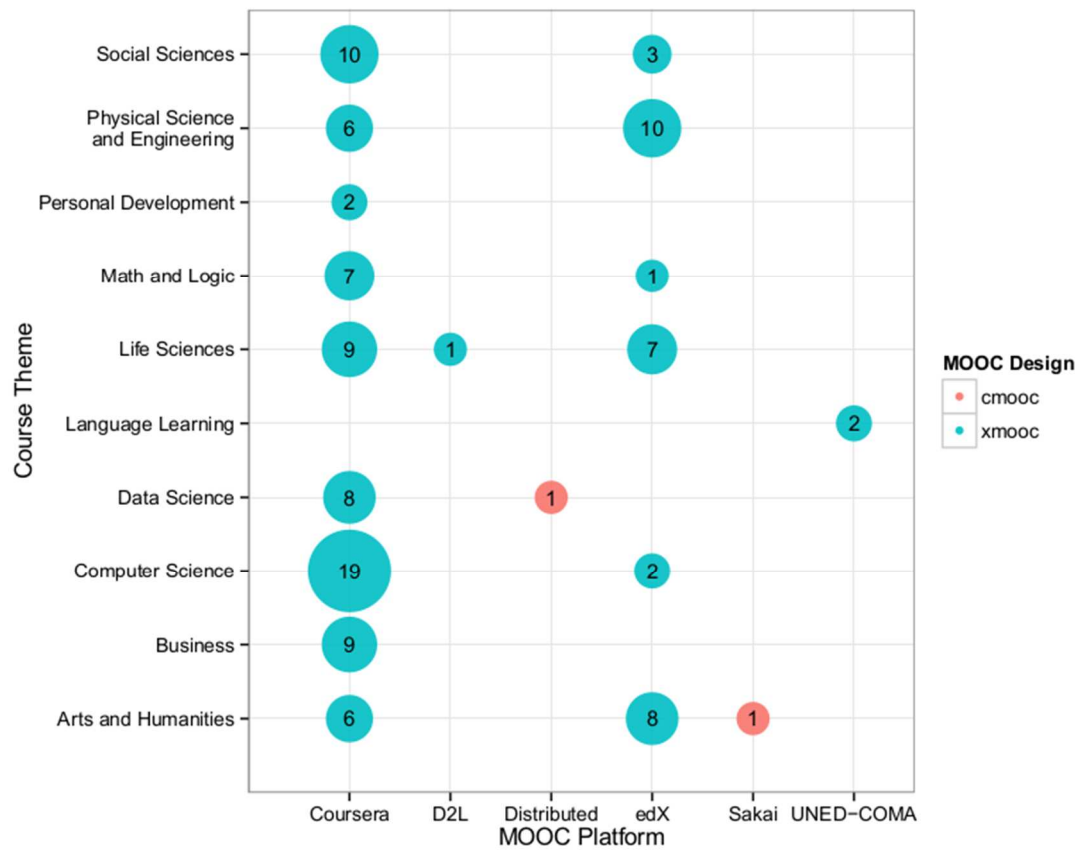
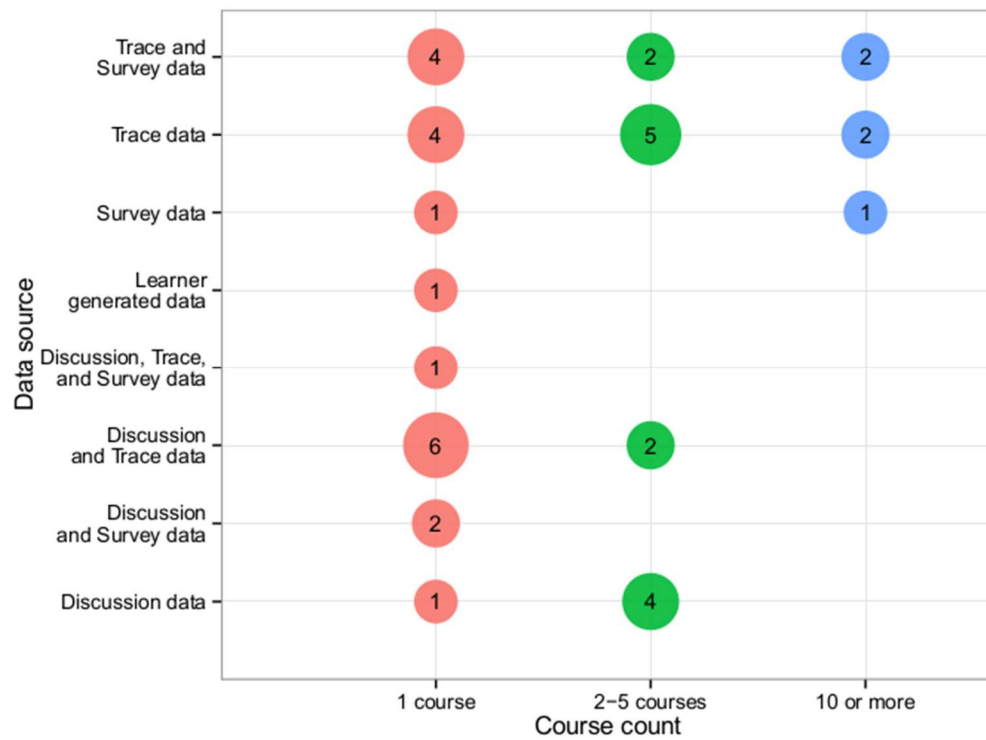
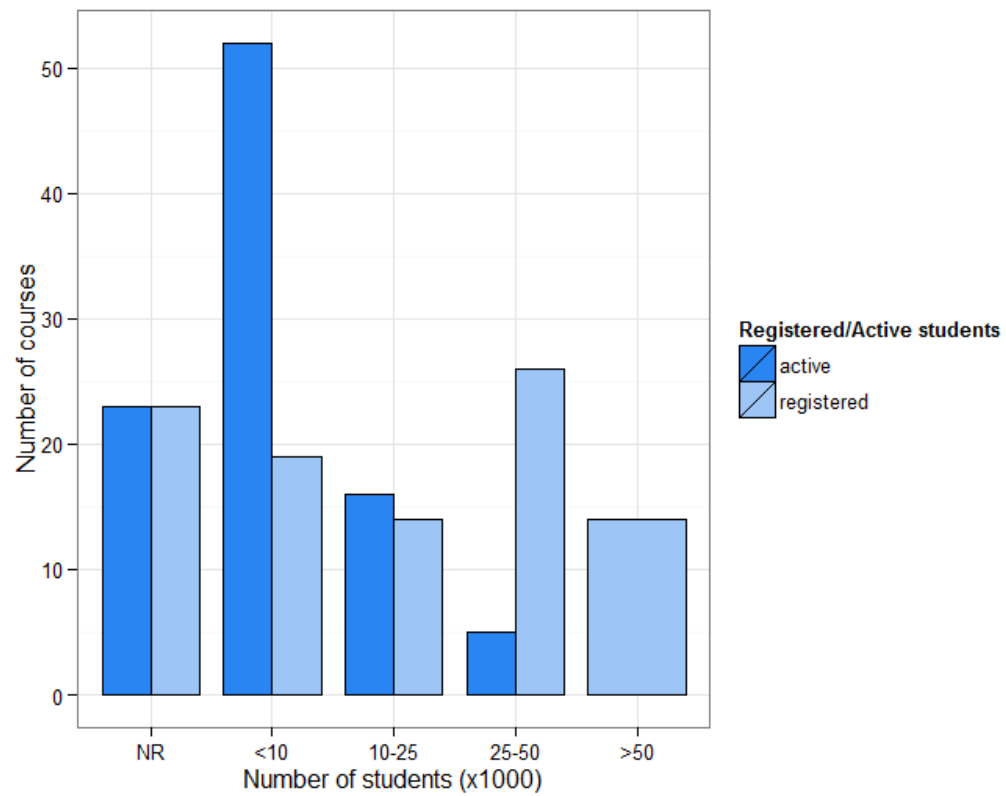


Figure 3. The number of studies within a given topic, delivered on a given MOOC platform, with colors indicating MOOC design (i.e., xMOOC or cMOOC).



*Figure 4.* The number of courses using different data sources with the number of courses included in the analyses.



*Figure 5.* The number of courses analyzed in the studies included in the review with the number of registered or active/observed students.

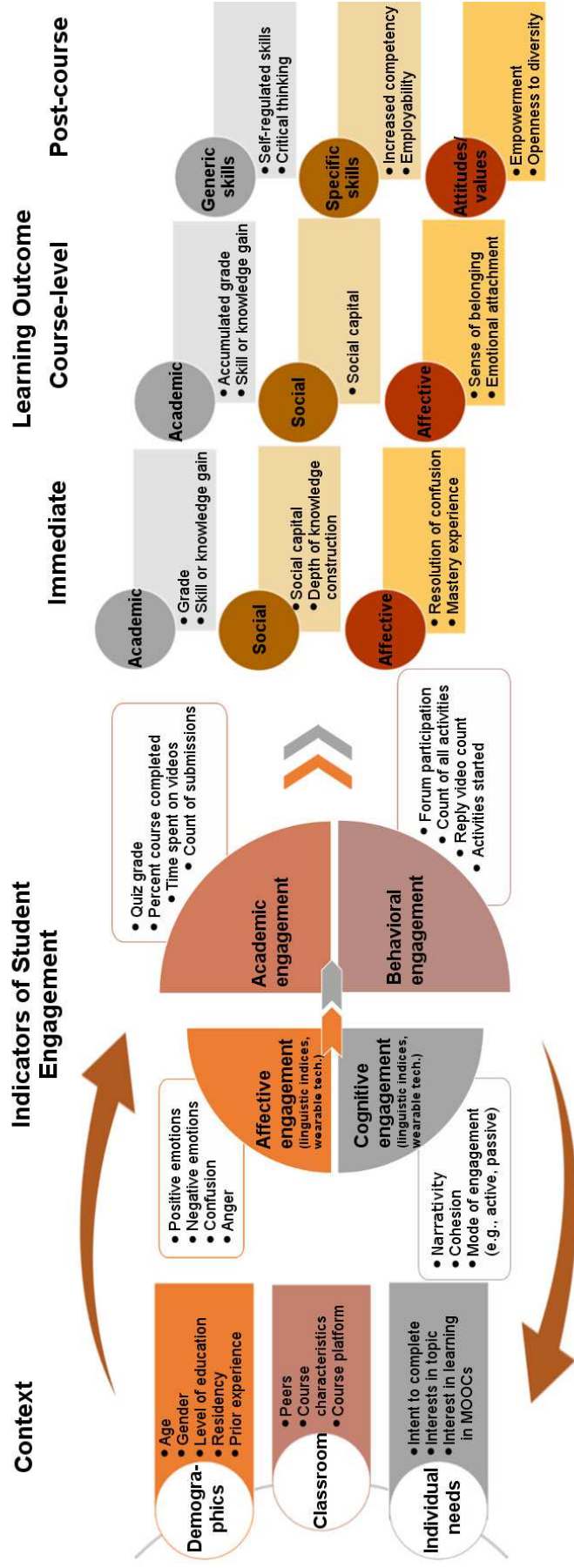


Figure 6. The adopted model of the association between context, engagement, and proximal learning outcome, originally developed by Reschly and Christenson (2012), with indicators specific for learning in non-formal, digital educational settings. Figure S1 depicts the original model, as proposed by Reschly and Christenson.



## Appendix A. Overview of the studies included in the systematic review

TABLE 1  
STUDIES INCLUDED IN THE ANALYSIS, WITH THE INFORMATION ABOUT THE AUTHOR(S), TITLE, PUBLICATION VENUE TYPE, NUMBER OF COURSES ANALYZED, DATA SOURCES USED, NUMBER OF PARTICIPANTS (REGISTERED, ACTIVE, COMPLETED), AND PUBLICATION YEAR

#	Study	Title	Publication Venue Type	Num. Courses	Data Sources	Registered	Num. of Students Active/Observed	Completed
1.	Adamopoulos (2013)	What makes a great MOOC? An Interdisciplinary Analysis of Student Retention in Online Courses	Conference	133	S	NR	842	NR
2.	Bergner et al. (2015)	Methodological Challenges in the Analysis of MOOC Data for Exploring the Relationship between Discussion Forum Views and Learning Outcomes	Conference	1	T-D	154,753	~50,000	7,157
3.	Boyer and Veeramachaneni (2015)	Transfer Learning for Predictive Models in Massive Open Online Courses	Conference	3	T	235,197	NR	11,243
4.	Brooks, Stalburg, et al. (2015)	Learn with Friends: The Effects of Student Face-to-Face Collaborations on Massive Open Online Course Activities	Conference	1	T-S	NR	NR	NR
5.	Brooks, Thompson, et al. (2015)	Who You Are or What You Do: Comparing the Predictive Power of Demographics vs. Activity Patterns in Massive Open Online Courses (MOOCs)	Conference	1	T-S	61,820	23,818 (4,130)	NR
6.	Champaign et al. (2014)	Correlating Skill and Improvement in 2 MOOCs with a Student's Time on Tasks	Conference	2	T-S	NR	6,960	8,187
7.	Coffrin et al. (2014)	Visualizing Patterns of Student Engagement and Performance in MOOCs	Conference	2	T	91,994	55,329	2,207
8.	Crossley et al. (2015)	Language to Completion: Success in an Educational Data Mining Massive Open Online Class	Conference	1	T-D	> 48,000	13,314	638
9.	Authors (2015b)	REMOVED FOR THE REVIEW	Conference	1	D	16,091	1,754	517
10.	Engle et al. (2015)	Coursera's Introductory Human Physiology Course: Factors that Characterize Successful Completion of a MOOC	Journal	1	T-D-S	33,378	15,000	NR
11.	Gillani and Eynon (2014)	Communication Patterns in Massively Open Online Courses	Journal	1	D-S	8,700	4,337	NR
12.	Goldberg et al. (2015)	Relationship between Participants' Level of Education and Engagement in their Completion of the Understanding Dementia Massive Open Online Course	Journal	1	D-S	13,950	NR	6,520

#	Study	Title	Publication Venue Type	Num. Courses	Data Sources	Registered	Num. of Students Active/Observed	Completed
13.	Greene et al. (2015)	Predictors of Retention and Achievement in a Massive Open Online Course	Journal	1	T-S	33,938	3,875	1,097
14.	Heutte et al. (2014)	MOOC User Persistence Lessons from French Educational Policy Adoption and Deployment of a Pilot Course	Journal	1	T-S	1,189	917	*NA
15.	Jiang, Warschauer, Williams, O'Dowd, and Schenke (2014)	Predicting MOOC Performance with Week 1 Behavior	Conference	1	T-D	37,933	NR	2,522
16.	Jiang, Fitzhugh, and Warschauer (2014)	Social Positioning and Performance in MOOCs	Conference	2	D	163,100	4,706	NR
17.	Authors (2015a))	REMOVED FOR THE REVIEW	Conference	1	L	NR	1,426	*NA
18.	Kennedy et al. (2015)	Predicting Success: How Learners' Prior Knowledge, Skills and Activities Predict MOOC Performance	Conference	1	T	37,777	22,731	774
19.	Kizilcec and Halawa (2015)	Attrition and Achievement Gaps in Online Learning	Conference	21	T-S	513,098	120,854	NR
20.	Kizilcec and Schneider (2015)	Motivation as a Lens to Understand Online Learners: Toward Data-Driven Design with the OLEI Scale	Journal	14	T-S	295,355	71,475	NR
21.	Koedinger et al. (2015)	Learning is Not a Spectator Sport: Doing is Better than Watching for Learning from a MOOC	Conference	1	T	27,720	14,264	1,154
22.	Konstan et al. (2015)	Teaching Recommender Systems at Large Scale: Evaluation and Lessons Learned from a Hybrid MOOC	Journal	1	S	28,389	21,357	5,643
23.	Li et al. (2015)	MOOC Video Interaction Patterns: What Do They Tell Us?	Journal	2	T-S	NR	31,880	5,539
24.	Loya et al. (2015)	Conscientious Behaviour, Flexibility and Learning in Massive Open On-Line Courses	Journal	1	T	50,335	29,950	10,398
25.	Ramesh et al. (2014a)	Learning Latent Engagement Patterns of Students in Online Courses	Conference	1	T-D	NR	1,665	826
26.	Ramesh et al. (2014b)	Uncovering Hidden Engagement Patterns for Predicting Learner Performance in MOOCs	Conference	3	T-D	> 65,000	27,500	7,000
27.	Santos et al. (2014)	Success, Activity and Drop-outs in MOOCs an Exploratory Study on the UNED COMA Courses	Conference	2	T	56,876	6,252	2,722
28.	Sharma et al. (2015)	Identifying Styles and Paths toward Success in MOOCs	Conference	4	T	NR	NR	NR
29.	Sinha and Cassell (2015)	Connecting the Dots: Predicting Student Grade Sequences from Bursty MOOC Interactions over Time	Conference	13	T	NR	10,000	NR
30.	Tucker et al. (2014)	Mining Student-Generated Textual Data in MOOCs and Quantifying Their Effects on Student Performance and Learning Outcomes	Journal	1	T	NR	NR	NR

#	Study	Title	Publication Venue Type	Num. Courses	Data Sources	Registered	Num. of Students Active/Observed	Completed
31.	Vu et al. (2015)	Relational Event Models for Social Learning in MOOCs	Journal	1	T-D			
32.	X. Wang et al. (2015)	Investigating how Student's Cognitive Behavior in MOOC Discussion Forums Affect Learning Gains	Conference	1	T-D	66,286	33,527	NR
33.	Wen, Yang, and Rose (2014b)	Linguistic Reflections of Student Engagement in Massive Open Online Courses	Conference	3	D	27,750	491	NR
34.	Wen, Yang, and Rose (2014a)	Sentiment Analysis in MOOC Discussion Forums: What does it Tell us?	Conference	3	D	NR	5,512	NR
35.	Whitehill et al. (2015)	Beyond Prediction: First Steps Toward Automatic Intervention in MOOC Student Stopout	Conference	10	T	245,034	NR	20,056
36.	Yang, Wen, Kumar, Xing, and Rose (2014)	Towards an Integration of Text and Graph Clustering Methods as a Lens for Studying Social Interaction in MOOCs	Conference	2	T-D	NR	NR	NR
37.	Yang et al. (2015)	Exploring the Effect of Confusion in Discussion Forums of Massive Open Online Courses	Journal	3	D	NR	NR	NR
38.	Ye et al. (2015)	Behavior Prediction in MOOCs using Higher Granularity Temporal Information	Conference	2	T	NR	NR	NR

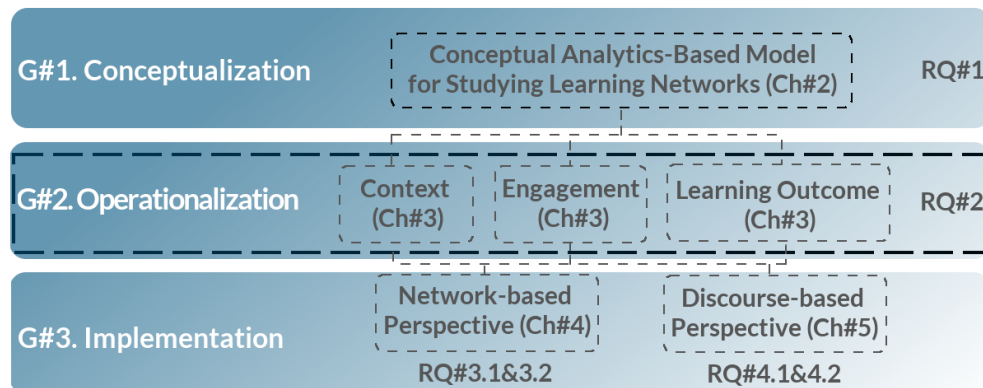
*Note:* Publication Venue Type – Conference (C), Journal (J). NR – Note Reported.

\* Given that those studies analyzed courses based on the connectivist pedagogy, we reported a number of students who completed a course as NA (Not applicable).

\*\* Data Sources: T – trace data, D – discussion data, S – survey data, L – learner generated data (e.g., blogs, tweets, Facebook posts).

### 3.3 Engagement as a part of the conceptual analytic-based model

In this chapter, I provided a redefinition of the existing educational framework that describes an association between context, learner engagement and learning outcome, to account for specific aspects of studying learning networks emerging from learning with MOOCs. Specifically, the study introduced in [Section 3.2](#) argues that engagement in learning networks should be observed as a multi-dimensional construct, comprised of academic, behavioral, cognitive, and affective engagement. Moreover, engagement also mediates the association between contextual factors (i.e., learners' demographics, classroom, and learner individual needs) and learning (i.e., academic, social, and affective) outcome.



**Figure 3.1.** Overview of the thesis structure across the three main goals identified in the present research, with the highlighted focus of the second chapter.

In the context of the proposed conceptual analytics-based model introduced in [Chapter 2](#), this chapter, and particularly study introduced in [Section 3.2](#), represents an operationalization of the key constructs of the assessment for learning in networks ([Figure 3.1](#)). Moreover, through the second part of this thesis ([Chapter 4](#) and [5](#)), I present five empirical studies that propose several learning analytics methods for measuring learner engagement in different educational settings. Those studies rely on different types of engagement, as well as, on various aspects of the model of the association between context, engagement, and outcome (introduced in the previous section) to provide means for measuring properties of the conceptual analytics-based model presented in [Chapter 2](#). Speaking in terms of the ECD model, [Section 3.2](#) provides evidence about student model variables ([Mislevy et al., 2003](#)).

It is important, however, to note that the mapping between the conceptual analytics-based model introduced in [Chapter 2](#) (i.e., student model) and the model of the association between context, engagement, and outcome ([Section 3.2](#)) (i.e., evidence model) is not always straightforward. Whereas the association between the contextual variables on the one hand, and personal characteristics and context on the other one, could be easily interpreted, explaining the notion of *structure* is somewhat more complex. Structure of interactions in learning networks is primarily assessed by observing social (or socio-technical) interactions among network actors. Given that behavioral engagement focuses on participation and persistence, it also represents primary means for assessing the nature and structure

of interactions in the emerging learning network. In that sense, the behavioral engagement as introduced in [Section 3.2](#), encompass what, [Pekrun and Linnenbrink-Garcia \(2012\)](#) defined within two distinct dimensions as behavioral (e.g., persistence in the course) and social-behavioral (e.g., interaction with peers) engagement.

In redefining and re-operationalizing the original model of the association between context, engagement, and outcome, as proposed by [Reschly and Christenson \(2012\)](#), I focused on measuring cognitive and affective engagement relying on learning analytics methods that would allow for assessment for learning in networks. This further means that cognitive and affective engagement are currently structured in a way to provide insight into the quality of learner generated discourse analyzing language and content of artefacts produced in the learning process ([Section 3.2](#)). However, recent progress in advances in automated measurement of engagement during learning from machine-readable behavioral and psychological signals, such as eye tracking, electrodermal activity, or facial expressions ([D'Mello et al., 2017](#)), should allow for a wider adoption of the complex assessment of cognitive and affective engagement in networked learning settings such as with MOOCs. Therefore, the model proposed in [Section 3.2](#) accounts for the multimodal data sources. Nevertheless, given that their application is still widely limited to the more formal educational context and laboratory settings ([Ocumpaugh et al., 2014](#); [Pekrun and Linnenbrink-Garcia, 2012](#)), these are not further discussed as means to operationalize conceptual analytics-based model introduced in this thesis.

The notion of observing engagement as a process and an outcome, reflects the idea of including *dynamics* as one of the factors in understanding learning networks. As outlined in the following two chapters, each of the studies included in this thesis accounts for some form of the evolution of discourse being produced in the learning process or the emergence of specific structures of social interactions. As argued here and elsewhere learning is a process ([Illeris, 2007](#)). It is through the process of learning that discourse and interactions between learners evolve throughout the course ([Goodyear and Carvalho, 2014a](#); [Jones, 2015](#); [Eynon et al., 2016](#)). Therefore, the part of the model introduced in the previous section that argues for observing engagement as a process aligns with the notion of temporality and *constant change* of the constructs that define learning networks.

### 3.4 Summary

This chapter introduces the model of the association between context, engagement, and learning outcome that represents a specific operationalization of the conceptual analytics-based model for assessment for learning in MOOCs. This model stems from the comprehensive body of research on learner engagement in formal (i.e., face-to-face and traditional online) learning settings and is adopted to account for specificities of learning with MOOCs. The engagement model introduced in this chapter recognizes contextual factors as being grouped around demographic and classroom related data, as well as through learners' individual needs and goals. It further defines engagement as a multidimensional construct comprised of academic, behavioral, cognitive, and affective engagement, that could be ob-

served as a process or as an outcome. Finally, the model (Section 3.2) moves beyond observing only academic assessment as primary approach to measure learning success, arguing for the importance of social and affective dimension of learning outcome.

The second part of my thesis introduces five empirical studies that rely on different aspects of the engagement model to provide means for understanding factors that describe learning networks - i.e., structure, discourse, and dynamics. In so doing, each study brings another level of complexity as means of pointing out to the importance of considering proposed constructs interchangeably, measured using different aspects of learner engagement (Sinatra *et al.*, 2015; D'Mello *et al.*, 2017).

# Social Interaction-Based Perspective on Studying Learning Networks

## 4.1 Preface

[Chapter 4](#) and [Chapter 5](#) illustrate the application of the proposed conceptual analytics-based model introduced in the first part of this thesis, through the series of empirical studies on learning networks emerging from various (structured or distributed) MOOC settings. Each chapter offers a novel analytics-based approach to examining structural and discourse properties of learning networks. In so doing, every study relies on a subset or all four engagement types introduced in [Section 3.2](#) (i.e., cognitive, affective, behavioral, and academic), whereas chapters are structured in a way to show the importance of considering all model components interchangeably, as well as emphasizing relevance of considering context in which learning occurs.

This chapter, introduces three studies that primarily utilize social interaction-based perspective in studying learning networks. With the technological advancements in recent years, learning in digital age occurs in networks through social interactions with our peers and utilization of available resources and technological affordances ([Siemens, 2008](#); [Eynon et al., 2016](#)). Therefore, contemporary learning theories and approaches (e.g., distributed cognition, communities of practice or connectivism) posit that learning is no longer an isolated individual process, as argued in traditional theories of learning ([Siemens, 2008](#); [Siemens et al., 2015](#); [Eynon et al., 2016](#)). In such conceptualization, it seems crucial to understand what emerging roles learners (and teachers) attain in these interactions and who tends to learn with whom in distributed settings ([Siemens et al., 2015](#); [Eynon et al., 2016](#)). Moreover, to support teaching and improve learning, it is also important to understand factors (learning-related and contextual) that would lead towards better educational experience ([Garrison, 2011](#); [Moore, 1993](#)). Finally, given the large scale data about student learning and rather contradictory findings with respect to what factors are important (i.e., significant) predictors of learning and learning success, it is important to understand when and to what extent we can rely on observed measures of learning to make informed decisions about learning in networks.

In addressing those challenges, I start with exploring emerging roles learners and teachers occupy in the process of learning in distributed MOOC context, such as with connectivist MOOCs ([Section 4.2](#)). In the broader context of computer supported collaborative learning in general, roles have been considered a key aspect of learning in collaborative settings ([Hoadley, 2010](#); [Strijbos and Weinberger, 2010](#)). In learning with MOOCs, however, studying structure of communication between course participants became (at least) equally relevant, given the opportunities this learning context offers for connecting learners “from diverse geographical locations with varied experience to participate and collaborate with each other without physical presence” ([Eynon et al., 2016](#), p.2). On the other hand, this diverse educational context, where learners usually interact over a short period of time, brings another challenge for developing more sustained communication and perceived social presence of peer learners ([Poquet and Dawson, 2016](#)). Finally, in the particular case of connectivist MOOCs, examining patterns of social (and socio-technical) interaction could help contribute towards understanding the main principles of connectivism as a theory of learning. Therefore, the study introduced in [Section 4.2](#)



focuses on exploring *structure* of socio-technical interactions and *dynamics* of their change in a context of distributed learning settings, the two dimensions of the student (i.e., conceptual) model introduced in [Chapter 2](#). As part of the operationalization of the proposed task model ([Chapter 2](#)) and driven by the principles of connectivist learning theory, this mixed methods study observes the evolution of social structures to identify the most influential social and technical factors that frame information flow and the knowledge building processes in the network of learners emerging from interactions within the context of specific social media platform used (i.e., Twitter). In so doing, I observed metrics of students' *behavioral engagement* – such as, frequency of posting to a social media platform – and *contextual factors* – such as student demographics and media in use, as introduced in the evidence model ([Chapter 2](#)) and operationalized in [Chapter 3](#).

Building further on this approach ([Section 4.2](#)), the following section ([Section 4.3](#)) introduces a study that accounted for certain aspects of learners' social identity, as being depicted in learner generated discourse from communication in MOOC settings ([Section 4.3](#)). Specifically, the study employed advanced statistical models to examine the importance of learners personal identity and contextual factors (such as social media used) for the development of social capital, as a form of learning outcome in learning networks ([Section 3.2](#)). The study detailed the role of language and media affordances as means to reveal important aspects of human activity in online social interaction. From the perspective of the analytics-based model introduced in previous chapters ([Chapter 2](#) and [Chapter 3](#)), the study presented in [Section 4.3](#) observes *structure* of social interactions, *discourse* produced through the processes of knowledge sharing and knowledge building, accounting for the *temporal aspect* and evolution of discourse and structure. As such, the publication introduced in [Section 4.3](#) accounts for all three key constructs defined in the student model introduced in [Chapter 2](#). On the other hand, observing through the model of the association between context, engagement and learning outcome ([Section 3.2](#)), and the evidence model presented in [Section 2.2](#), here I account for *cognitive* and *behavioral* engagement, along with the *contextual factors* (such as media use and time of the course), whereas learning outcome was structured as *academic* (i.e., final course grade) and *social* (i.e., social capital developed through the course). From the perspective of the definition of the task model ([Chapter 2](#)), the work introduced in [Section 4.3](#) observes a broad set of social media in which interactions occur.

The first two studies introduced in this chapter ([Section 4.2](#) and [Section 4.3](#)), primarily focused on social outcomes, as defined in [Section 3.2](#), and the identification of factors that lead towards the specific position in a social network. Specifically, what are the social (or socio technical) aspects of communication in distributed educational settings and properties of learners' social identity that influence someone's position in the network of learners. To a certain extent, such an approach was legitimate given that we observed learning networks in the context of connectivist MOOCs that do not assume any of the traditional forms of assessment ([Siemens, 2005](#); [Kop, 2011](#)). Therefore, a similar approach (as in [Section 4.2](#) and [Section 4.3](#)) was also applied in a centralized MOOC. Specifically, [Dowell et al. \(2015\)](#) aimed at predicting two different achievement measures - final course grade, as a form

of academic outcome, and social centrality, as a form of social outcome - using linguistic properties of student generated content. Results showed that the linguistic characteristics positively associated with social centrality were negatively associated with the final course grade, and vice versa.

Although we did not directly compare student social outcome with academic outcome, the findings presented in [Dowell et al. \(2015\)](#) suggest that these two measures of learning tend to capture different achievement metrics, suggesting further that “the skills associated with these two learning-related outcomes differ” (*ibid.*, p.256). On the other hand, although some of the learners managed to attain structurally more advanced positions compared to their peers, these results could suggest that they also failed to utilize those benefits. Therefore, the third study introduced in this chapter highlights the importance of contextual determinants in framing social interactions in learning networks. Research and practice in learning analytics commonly relies on general models (i.e., context independent) in order to inform learning and teaching processes, predict learning outcomes, or provide appropriate scaffolds ([Gašević et al., 2016](#)). However, without considering contextual factors, an analysis can lead to incomplete and sometimes contradictory conclusions ([Wise and Shaffer, 2015](#); [Dawson et al., 2015](#)). In order to provide for more valid inferences and identify the determinants that provide contextually salient understanding of learning in networks, I studied social dynamical processes that frame human-human interactions, in the context of learning with MOOCs. Framed around the sociological theory of social interactions ([Simmel, 1950](#)) and utilizing statistical network analysis, the study presented in [Section 4.4](#) relies on statistical networks analysis to examine *dynamics* of social *structure* development (as defined within the student model - [Chapter 2](#)) in the context of two MOOCs delivered within a single platform (i.e., Coursera) (as defined within the task model - [Chapter 2](#)). From the perspective of model operationalization ([Chapter 3](#)) and evidence model introduced in model definition ([Chapter 2](#)), in addition to the contextual factors, the study also observes learners’ *behavioral engagement* and the association between *social* and *academic outcome*.

## 4.2 Publication: Roles of course facilitators, learners, and technology in the flow of information of a CMOOC

The following section includes the verbatim copy of the following publication:

Skrypnyk, O., [Joksimović, S.](#), Kovanović, V., Gašević, D., and Dawson, S. (2015). Roles of course facilitators, learners, and technology in the flow of information of a CMOOC. *International Review of Research in Open and Distance Learning*, 16(3) pp.188–217

June – 2015

## Roles of Course Facilitators, Learners, and Technology in the Flow of Information of a CMOOC

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### Abstract

Distributed Massive Open Online Courses (MOOCs) are based on the premise that online learning occurs through a network of interconnected learners. The teachers' role in distributed courses extends to forming such a network by facilitating communication that connects learners and their separate personal learning environments scattered around the Internet. The study reported in this paper examined who fulfilled such an influential role in a particular distributed MOOC – a connectivist course (cMOOC) offered in 2011. Social network analysis was conducted over a socio-technical network of the Twitter-based course interactions, comprising both human course participants and hashtags; where the latter represented technological affordances for scaling course communication. The results of the week-by-week analysis of the network of interactions suggest that the teaching function becomes distributed among influential actors in the network. As the course progressed, both human and technological actors comprising the network subsumed the teaching functions, and exerted influence over the network formation. Regardless, the official course facilitators preserved a high level of influence over the flow of information in the investigated cMOOC.

**Keywords:** Teaching; socio-technical networks; social network analysis; MOOCs

## Introduction

There is much debate over the role of Massive Open Online Courses (MOOCs) in the contemporary education space (Daniel, 2014). Although perspectives differ when it comes to questions regarding the potential for MOOCs to provide an effective business model, or their perceived education quality, MOOCs are increasingly playing a greater role in the provision of adult education online. Diverse opinions about the scaling-up of the standard online practices have given rise to the discussions about the complexities of MOOC pedagogy, such as whether online peer interactions can be scaled to address learner diversity (Stewart, 2013), or the model of pedagogical design that is most suitable for this learning context (Rodrigues, 2012; Selwyn & Buffin, 2014).

Prior to the emergence of scaled online courses, numerous studies have identified that specific instructional strategies can effectively enhance learning gains, academic performance, and student satisfaction in online and distance education settings (Garrison & Cleveland-Innes, 2005; Lou, Bernard, & Abrami, 2006; Vrasidas & McIsaac, 1999). Along with course facilitation and direct instruction, instructional strategies constitute a level of teaching presence (Anderson, Rourke, Garrison, & Archer, 2001), that plays an important role in shaping of learners' online experience. For example, the well-known model of communities of inquiry (Garrison, Anderson, & Archer, 1999) posits that teaching presence is critical for establishing and sustaining cognitive presence and for shaping and maintaining the degree of social presence among learners (Garrison, 2011). In other words, teaching presence is instrumental to the facilitation of knowledge construction through engaged social interaction in a community of learners (Garrison, Cleveland-Innes, & Fung, 2010).

Although research related to the role of teachers has gained significant attention in online education, there are few academic studies that have extensively covered the general experiences and practices of teaching at scale (Liyanagunawardena, Adams, & Williams, 2014). Despite issues of scale, some of the findings may be transferable. In scaled online courses, teachers remain highly visible, although teaching function may be fulfilled in various ways, i.e. through information delivery in a recorded lecture, authored textbook, via facilitation of a synchronous video conference, through co-participation in online discussions, or even via an automated mailing list in MOOCs (Bayne & Ross, 2014). While there are multiple approaches for the design and delivery of MOOCs, the teaching practice can be situated on a spectrum ranging from highly centralized to highly distributed (ibid.).

Centralized MOOCs, often referred to as xMOOCs, are delivered via a learning management system with an emphasis on the teacher-chosen content. The course content is typically delivered through video lectures and often accompanied by online quizzes. In such courses, while online forum discussions are widely used, they primarily function as question and answer forums. In such contexts, the discussion forum – as a medium for facilitating social learning – is tangential

to the course pedagogy. In contrast, in distributed MOOCs, or cMOOCs, social knowledge construction, peer interaction, and learner-driven discussions are designed to be the centerpiece of the course design. Teachers of distributed MOOCs structure learning activities around learner-created artifacts underlining the importance of peer engagement and discussions that take place via different technologies. Learners are encouraged to use technologies of their choice, which constitute their personal learning environments. Social networking software such as Twitter and Facebook are commonly used tools for sharing, aggregating, and connecting information (Saadatmand & Kumpulainen, 2014).

This study set out to address the knowledge gap in understanding the teachers' role within the context of cMOOCs. We examined the positions taken up by learners, teachers, and the adopted technology in a distributed scaled online course "Connectivism and Connective Knowledge 2011"<sup>1</sup> (CCK11), and how they influence the flow of information within the course. Through the analysis of course participants' social networking positions over time, the study investigated participants' potential to influence the flow of information and community formation among learners. We focused on student interactions on Twitter social networking platform, as it was adopted by the majority of course participants and was suggested by course facilitators as the primary communication medium. In line with the socio-technical perspective (Creanor & Walker, 2010), we constructed a course social network consisting of course participants (i.e., learners and instructors), as well as the nodes representing technological affordances of social networking platform (i.e., Twitter hashtags). To uncover the change in the network structure, a series of social network analyses (Wasserman, 1994) was performed.

The aim of the CCK11 course was to explore and examine the application of the ideas of connectivism and connective knowledge – a theoretical view on learning that is built on the premise that knowledge is activated through the process of learners connecting to and feeding information to the broader course community (Kop & Hill, 2008, p. 2). The course ran for twelve weeks, and it was of interest to practitioners and researchers working in online education and to those facilitating online community development. Participation in the course was open, however those learners who wanted to receive a certificate had to apply for university admission and officially register their enrolment with the University of Manitoba<sup>2</sup>. For the analyses, we collected learner demographic data from their various online profiles and distributed course Tweets to reconstruct the evolution of the course.

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<sup>1</sup> <http://cck11.mooc.ca>

<sup>2</sup> <http://cck11.mooc.ca/about.htm>

# Literature Review

## Teaching in a Distributed MOOC

The core differences between various pedagogical designs of MOOCs lies in the provisions for learner autonomy and teacher control as embedded in the course design. Prior to the establishment of MOOCs, online learning was centered on the curriculum pre-defined by the teacher, and presented through a centralized technology (e.g., learning management system), with little pre-designed need for learners to experiment and connect outside of this technical system. The original offers of MOOCs – now known as cMOOCs and referred to as distributed MOOCs in this paper – diverged from the dominant, centralized course design and were organized as distributed courses utilizing many different online platforms. The design of cMOOCs centered on connecting learners by helping them find each other across the various distributed technological tools they were using to express their views on the course themes.

The high degree of learner autonomy afforded individuals opportunity to adopt a vast array of technologies to support their learning endeavors. This focus on the adoption of distributed tools imposed modifications on the teaching activities. That is the teachers needed to help learners meet and connect to each other. In doing so, facilitators of the first distributed courses encouraged students to explore the topic, and create a unique artifact using their preferred technologies that would constitute their personal learning environment. The official course facilitators then would use special software to aggregate these distributed activities in daily newsletters to help learners locate the content and each other, and “acquire learning for themselves, rather than have learning served to them by an alternate provider or institute” (Hollands & Tirthali, 2014, p. 33).

It was also theorized that course facilitators and learners should have an equal level of influence within the community (Downes, 2010). Both facilitators and learners would create artifacts in relation to each other’s ideas, opinions, and common course themes. Furthermore, while course facilitators would review, summarize, and reflect on the events of the course in their produced artifacts, so would the learners. Facilitators regularly sent out a course newsletter that included all web-based artifacts tagged by their authors with the course hashtag. As a result, any course participant could contribute to course discussions by marking their own content with the course hashtag.

It is important to note that this pedagogical design does not imply the elimination of the teacher’s function over time. As the discussions spread based on the growing connections between the course participants, the official course facilitator needs to draw students’ attention to certain content elements (Siemens, 2010). Facilitators are required to be constantly present to amplify, curate, filter, and guide community-driven sense-making and learning (ibid.). Still, due to the

distributed control embedded in the pedagogical design, any course participant could be doing exactly the same thing, as long as the other course participants follow their lead.

## **Investigating Teachers' Control through Structural Analysis**

Facilitating the creation of the network of learners and distributed control over the information flow, as a teaching practice, reflects the very premise of connectivist principles of learning, i.e. that knowledge is dispersed across the network of learners and occurs through the interactions between participants (Downes, 2012). To analyze the learning that takes place in a connectivist MOOC, a natural question from the perspective of knowledge construction is that of a quality of the interactions that take place. From a connectivist perspective, however, the initial question is whether the formation of the network, and its structure reflects the pedagogical intention.

Social network analysis (SNA) is used to capture and analyze the mechanisms underlying structures of learner and teacher interactions (Haythornthwaite & de Laat, 2012). Surprisingly, despite the broad popularity of SNA techniques for investigating MOOCs (Gasevic, Kovanovic, Joksimovic, & Siemens, 2014), there are few cMOOC studies that have applied SNA to examine the relationships and connections that occur between course participants in such environments. For example, Kop, Fournier, & Mak (2011) visualize the networks of learner and teacher interactions to highlight the complexity of course discussions in their evaluation of the PLENK10 cMOOC<sup>3</sup>. They report that in Moodle discussions the facilitator acts as an instigator of activity and is present along with active participants. The study does not provide any SNA metrics to support this observation. Similarly, Yeager, Hurley-Dasgupta, & Bliss (2013) exploit the visual power of SNA to reflect on their experience in teaching CMC11<sup>4</sup>. They measure eigenvector centrality of course participants to identify the relative influence of a node in a network, and conclude that a course facilitator and several other participants take on higher levels of activity and are central to the network. The authors describe this group as an active core that enabled its further success. This study offers a static aggregation of the network relationships as they took place by the end of the course, but does not provide insights into how the relationships between these nodes in the core were formed and evolved over time.

Certain inferences about the role of facilitator can be made from cMOOC research that does not utilize SNA. Based on the analysis of the PLENK10 cMOOC, Kop (2011) reported that the frequency of facilitators' postings decreased significantly overtime, while the frequency of participants' postings increased. Such indicators suggest a decrease in the activity of a course facilitator, but it is unclear whether the decline in facilitators' activity correlates with the decreased control over the direction of the conversations in the course, and consequently, its content.

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<sup>3</sup> PLENK10 stands for Personal Learning Environments, Networks, and Knowledge MOOC that took place in 2010; <http://connect.downes.ca/>

<sup>4</sup> CMC11 stands for Creativity and Multicultural Communication cMOOC that took place in 2011; <http://www.cdllprojects.com/cmc11blog/>

The current study sets out to exploit SNA of the development of course network overtime to gain additional insights about its active participants, as well as their influence on the network formation. From a network analytical perspective, structural positions of the participants as captured by established measures of centrality, indicate the degree of access to people and information within the network (Burt, 2000; Haythornthwaite, 2005; Homans, 1958; Wellman, 1997). This information can be used to indicate the varying degrees of control held by various individuals within flow of information in a network at different times of the course. The underlying structure for course communication indicates opportunities and limitation for access, the change of structure may also indicate a change of power (Burkhardt & Brass, 1990).

### **Inclusion of Technological Affordances**

It should be noted that cMOOC facilitators and learners are not the only agents that can influence how learners find, aggregate, and connect course information and participants. Stemming from the distributed nature of its pedagogical design, social networking software itself acts as a major enabling technology for cMOOCs by providing the certain affordances that foster information seeking and community formation. In the literature, Kop (2011) reports that in their evaluations of distributed courses, participants acknowledge the role Twitter played in humanizing learning, being instrumental to the creation of presence, and providing a “voice with the possibility to be listened to and to contribute to sense-making together with other participants”. These perceptions of the role technological affordances play in distributed MOOCs point towards an interdependent inseparable relationship between the social system of learners and the technical system of features of social media. For example, Twitter offers specific features that can directly influence the flow of information and community formation (Gruzd, Wellman, & Takhteyev, 2011) within the network of participants formed around a cMOOC. In this regard, Twitter hashtags are possibly one of the best examples for aggregating and facilitating the flow of information (Kop, Fournier, & Mak, 2011; Yang, Sun, Zhang, & Mei, 2012).

To analyse the potential to facilitate the development of a network – afforded by the social networking software used by course participants – we included Twitter hashtags as nodes into our network of course interactions. This is based on the sociotechnical perspective (Sawyer & Jarrahi, 2013) which affords a strong theoretical rationale for integrating technology into the creation of the structure that effectively enables course discussions. Socio-technical interaction framework (Creanor & Walker, 2010) treats social and technological dimensions as mutually constituted. In our particular context, treating both human participants and technological affordances as both capable of having reciprocal effect prevents the deterministic predictions about how a certain piece of technology provides specific affordances for a set pedagogy. Mutual constitution makes no prior judgment towards the importance of either social or technological aspects and requires analyzing the process of interactions as reciprocal between the contextual interactions and outcomes (Barrett, Grant, & Wailes, 2006).



## Research Questions

The aim of this study was to examine how a teaching function was fulfilled in a particular cMOOC, and i) whether official course facilitators maintain control and power over the information flow and influence content and direction of conversations; ii) whether other course participants emerge as fulfilling similar functions, and having significant impact over the flow of the course interactions; and iii) what is the role of technological affordances in fulfilling the teaching function related to shaping the interaction patterns of a distributed MOOC.

**RQ1.** What was the influence of course facilitators, course participants, and technological affordances on the flow of course discussions in Twitter-based interactions at different stages of a distributed MOOC?

We assumed that if social influence was distributed – as intended by the course facilitators – it would be reflected by the network structure through several emerged communities of learners, rather than being centered on course facilitators – as it would be the case in the teacher-controlled environment.

**RQ2.** Were there any emerging communities from Twitter-based interactions that frame course discussions? If so, who influenced their formation?

Addressing the research questions required reaching beyond the analysis of the sheer volume of user-generated content created and exchanged via social media (Kaplan & Haenlein, 2010). To make interpretations as to why certain structures underpinned the flow of information in this course, we also enquired who was referencing whom as a part of the exchange, and where these individuals were positioned in relation to other individuals and how the individual positions shifted along with the changes in the overall student network. To implement such analysis, we applied social network analysis measures to a series of course networks, representing week-to-week changes of the information flow, and complemented these with qualitative information concerning the learners.

## Methods

### Data Collection

The analyses for the presented study were conducted using the Twitter-based network of interactions. Although Twitter poses strict boundaries on the size of each post, it was the most utilised course communication tool. In their analysis of the same CKK11 course, Joksimovic et al. (2015) reported that – despite the wide use of blogs and Facebook in the course – Twitter afforded a significantly higher interactivity of conversations, and it was used by a greater number

of participants. This conclusion is also supported by the post-course reports from other cMOOCs, where participants indicated that Twitter was the most widely adopted tool and tweeting being ranked as the most frequent activity for learning and interaction (Kop, 2011; Saadatmand & Kumpulainen, 2014).

For the present study, we collected distributed asynchronous Twitter posts from the CCK11 course. The course was organized over a twelve-week period from January 17<sup>th</sup>, 2011 to April 11<sup>th</sup>, 2011. Course seminars featuring guest speakers were delivered using Elluminate (later rebranded as Blackboard Collaborate), while blog posts and tweets from participants were aggregated and distributed using gRSShopper<sup>5</sup>. In our data collection, we relied on daily newsletters aggregated by gRSShopper in order to obtain 2,483 tweets from more than 800 active participants. The collected data were stored in JSON format, with the information about authors' name, date/time created, media attached (e.g., photo, video, web page), mentions, and hashtags.

With respect to additional sources of data for this study, the CCK11 course did not include questionnaires for learners, on their personal goals, prior knowledge, nor research interests. All demographic data about Twitter participants were collected specifically for the purpose of this study and was retrieved manually from publicly available sources such as Twitter profiles, social networking sites (e.g., LinkedIn, About.me, and Blogger profiles), and through manual Web searches. The following demographic data were found relevant for an overview of course participants, and are presented in Figure 1: i) domain of work (e.g., secondary education, higher education, and health) in 2011, ii) type of work (e.g., research or practice) in 2011, iii) demographic data (e.g., location, gender, and professional background) in 2011.

As Figure 1 shows, the majority of participants were from Europe and North America and those include students from a wide variety of professions. Similarly, there were many South American, Australian, and New Zealand researchers and practitioners from the higher education. In contrast, there were few participants from Africa and Asia. Most participants had an education-related background either through formal credentialing or extensive work experience. The most frequent work domain for CCK11 participants was observed to be in higher education, with jobs ranging from practitioners in e-learning departments to academics. Another large group of participants was related to the commercial sector: implying that they were entrepreneurs, self-employed, or employed in a business or a company. The third largest group was secondary school teachers, followed by the group of English language instructors. They were grouped as "language professionals", unless their jobs fell within the domain of English for Academic Purposes and implied higher socialization into academia. The general demographics of the course participants is similar to those reported in the research literature on xMOOCs, with high numbers of educated participants with professional backgrounds in the course's subject (Ho et al., 2014; MOOCs@Edinburgh Group, 2013; Open UToronto, 2013).

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<sup>5</sup> <http://grsshopper.downes.ca/>

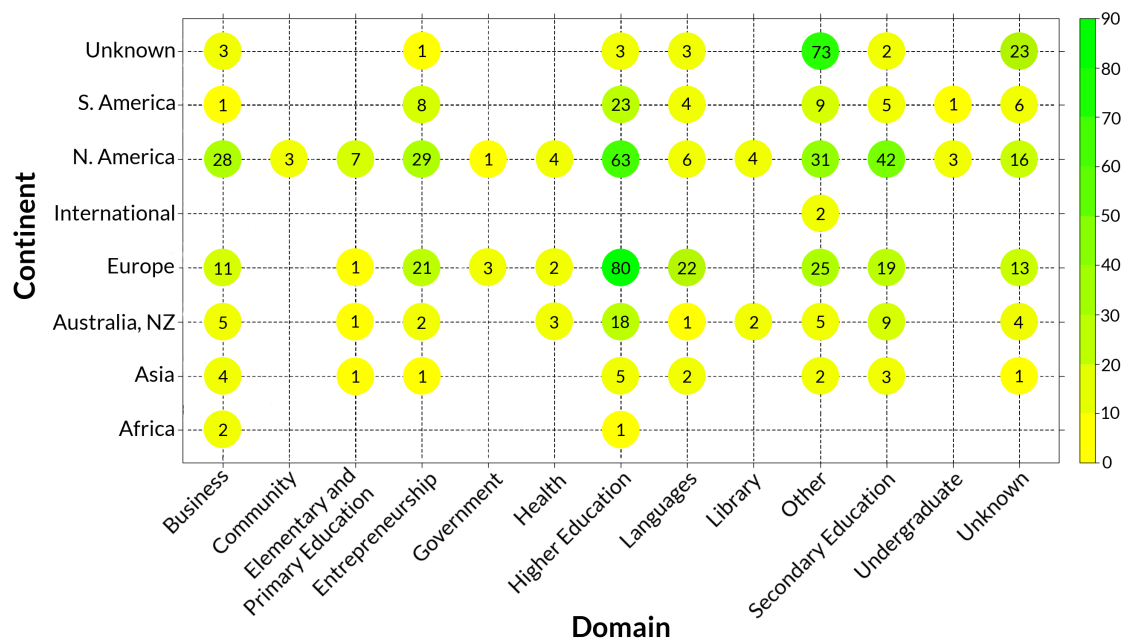


Figure 1. Summary of professional background and geographical locations of the participants in the large connected component of the course's network.

## Social Network Analysis

We constructed an information exchange socio-technical network (Jamali & Abolhassani, 2006) by including all authors and adopted hashtags into the graph as nodes in the network. The network was directed, and the edge (a link between two nodes) from author @A to author @B was created in cases when author @A mentioned author @B in their tweet, whereas the edge from author @A to hashtag #C was created in cases where author @A mentioned hashtag #C in their tweet. In all cases, edge weights were calculated based on the count of links between two nodes.

The constructed network was analyzed with the common social network analysis measures (Freeman, 1979; Watts & Strogatz, 1998):

- Closeness centrality (all, input and output) – represents the distance of an individual node in the network from all other nodes,
- Betweenness centrality – a measure of nodes brokerage opportunities, i.e., the importance of a given node in mediating communication between other nodes,

- Authority weight – nodes pointed to by many other nodes,
- Hub weights – nodes that link to many nodes with high authority weights,
- Weighted degree (all, input and output) – the count of edges a node has in a network, and
- Modularity over large connected components – a measure of decomposability of the network into modular communities.

To address the first research question, we conducted social network analysis at the node-level. SNA centrality measures of closeness and betweenness, hub and authority weights, and weighted degree for each individual weekly were calculated. Plotting the changes in these metrics over-time was used to identify changes in the network structure for both learners and hashtags.

To address the second research question, we conducted analysis at the network-level. First, we applied a modularity algorithm for community detection (Newman, 2006). An initial analysis revealed more than 130 communities, with several large communities and a significant number of small communities. These small communities usually contained one to five isolated nodes, created from tweets that did not include any of widely accepted hashtags and did not mention other learners. By first identifying weakly connected smaller parts of the network, and then partitioning it, we extracted the largest connected component (LCC), which contained more than 85% of nodes from the initial network. Further analyses, using the modularity algorithm were conducted on the largest connected component. This analysis detected 19 communities.

To understand which nodes and individuals were instrumental in the emergence of these 19 communities, we retrospectively tracked the emergence of these sub-networks in earlier weeks of the course, and identified the individuals and hashtags that initiated and sustained the development of the structure for these sub-networks.

All social network measures and the modularity algorithm were computed using Pajek64 3.15, a tool for social network analysis and visualization (Batagelj & Mrvar, 2004).

## Analysis

### Evolution of Influence in Information Flows

Research question 1 aimed to identify the sites of influence in the cMOOC network. To address this question the node-level analyses focused on both the social and technical elements that shaped the flow of information in the course under investigation. The purpose here was to identify the nodes that occupied structural positions that enabled them to exert a stronger influence over the flow of information within the course discussions. As described below, in-

degree, out-degree, closeness, betweenness, and hub and authority centralities were calculated for each course participant weekly.

First, the most prolific nodes (Table 1) were identified by measuring weighted out-degree, associated with the number of tweets the participants made, and thus, implying certain “loudness” and “visibility” for the other course participants. Out-degree implied that a person posted out-going information, such as shared a link to their blog post, asked a question, or re-shared somebody else’s link. Since hashtags do not exercise such activities on their own, only social nodes had the weighted out-degree, and not the technical ones. The total numbers of tweets produced during the course by the most prolific social nodes are listed in Table 1.

The Twitter account associated with the highest number of tweets was @cck11feeds. It was used by course instructors to fulfill one of the facilitation roles in the cMOOC – information aggregation (Siemens, 2010). None of the remaining “most” prolific nodes were associated with any of the assigned guest speakers or original course facilitators for the cMOOC, as revealed by the analysis of the demographic data (Table 1). Interestingly, additional time-based analysis of positions of the most prolific learners showed that learners who ranked high in producing content in the second half of the course were not very active within the first weeks. This may be explained by early course experiences being “overwhelming and chaotic”, since learners were facing potentially new concepts and technologies (Siemens, 2010). The demographic data further indicated that the leaders in content production on Twitter were dispersed throughout the main locations of CCK11 participants: Australia and New Zealand, North America, Europe, and South America. The professional domains of the most prolific course Twitter participants were practice-related, and are representative of profiles found in the course.

Table 1

*Distribution of Weighted Output Degree for Weeks 1, 5, 6, and 12 with the Demographic Data for the Top 10 Ranked Nodes within the Last Week*

Node	W1	W5	W6	W12	Description	Domain
@cck11feeds	0	282	447	1160	Course Aggregator	
@web2oeducation	0	117	147	929	European Teacher	Secondary School
@profesortbaker	0	281	330	404	South American English Teacher	Higher Education
@smoky_stu	0	46	82	306	Australian IT Teacher	Secondary School
@pipcleaves	23	128	139	208	Australian Educational Consultant	Entrepreneurship
@vanessavaile	0	77	86	196	Social Media Content Curator	Higher Education
@profesorbaker	0	121	136	147	South American English Teacher	Languages
@shellterrell	0	105	133	146	North American English Teacher	Entrepreneurship
@blog4edu	0	100	128	141	International Organization	Various
@suifaijohnmak	0	63	69	134	Australian Teacher of Logistics	Higher Education

After identification of the social nodes producing the majority of the content, we located nodes with the highest level of popularity (Table 2). Popularity was measured based on the weighted in-degree, which measures the number of times the node was referred to or mentioned. The rankings in Table 2 are based on values in the last week of the course, and reveals that the top ten most popular nodes primarily included technical (i.e., hashtags) nodes of the network. Only one social (@profesortbaker) node was found in the list of the most popular, while others were hashtags used to mark different topics within the course. We can also observe that most participants used the course hashtag #cck11 making that node most popular in the network, the same position taken by the course Twitter account by the amount of activity in the course based on weighted out-degree.

Table 2

*Distribution of Weighted Input Degree for Weeks 1, 5, 6, and 12, for the Top 10 Ranked Nodes within the Last Week*

Node	W1	W5	W6	W12
#cck11	29	861	1052	1982
#edchat	0	224	268	454
#eltchat	0	213	270	320
@profesortbaker	0	127	160	174
#edtech20	0	17	24	161
#edtech	0	60	72	154
#elearning	0	25	26	145
#education	0	54	62	110
#connectivism	2	27	31	100
#eadsunday	6	34	51	89

In line with prior research on hashtag affordances (Yang et al., 2012), we have observed that initially hashtags were used to mark shared information. Over time the functionality of hashtags extended, as some participants repeatedly used the same hashtags, indicating the formation of a community and a means for identifying to others an opportunity to engage. For example, hashtag #eltchat is the third most commonly referred topic theme in the last week of the course. It is used in week 2 for the first time by one person – @profesortbaker – a higher education practitioner specialized in teaching English as the second language (TESOL) who was identified as a highly popular node based on his weighted in-degree value. Within the weeks to follow, #eltchat was adopted by a large number of other participants. These were English teaching professionals (over forty individuals) of all levels who participated in the course. #eltchat (English language teaching chat) identified them as a professional group and contributed to gradual promotion of this hashtag. We observed similar dynamics in the popularity growth with #edtech20 initiated in the middle of the course by highly active but not yet well-connected node @web2oeducation; or with #elearning that was picked up in the fourth week of the course by two visible and highly prolific nodes, i.e., @daisygrisolia and @pipcleaves.

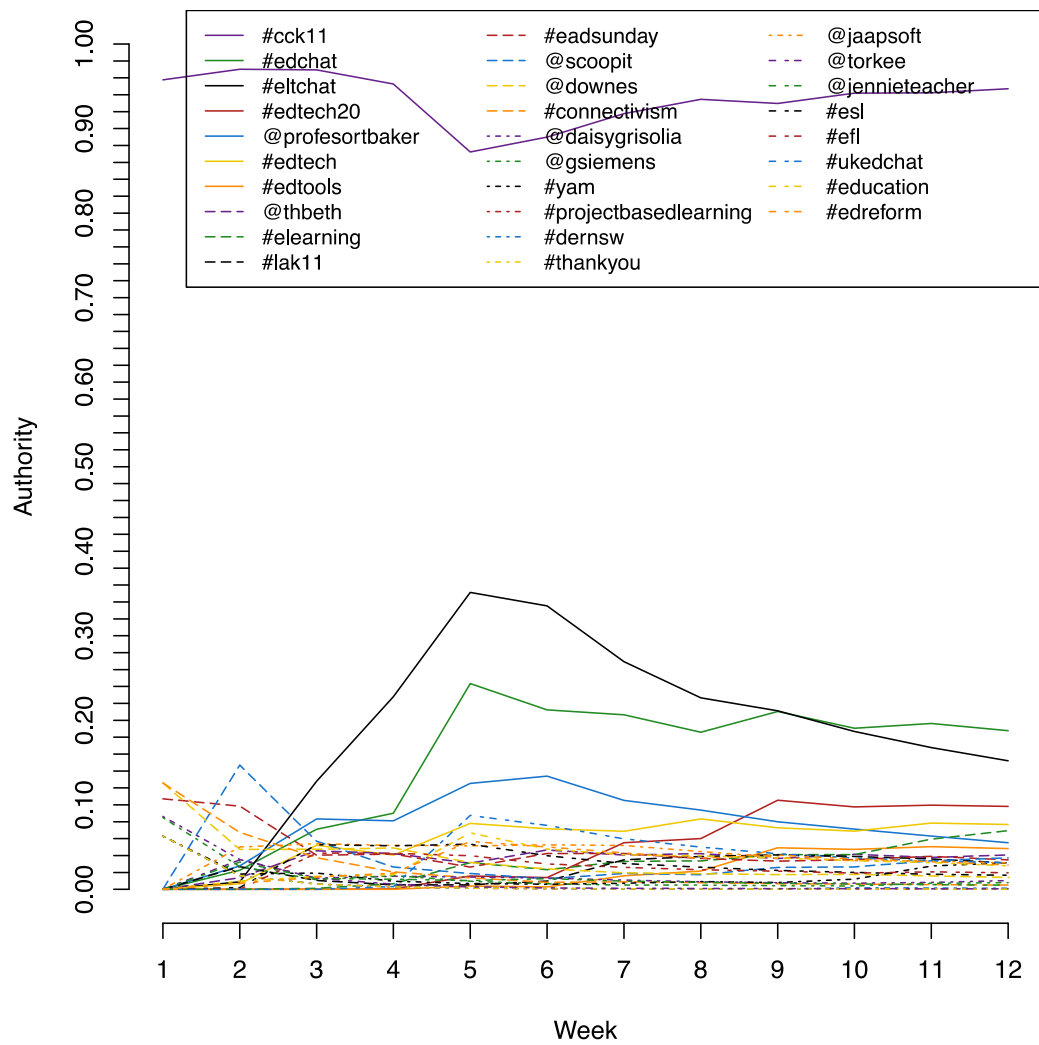
Next, hub and authority weights were calculated for each social and technical node in the network (Figure 2, Figure 3, and Figure 4). While Figure 2 shows the variation of authority weights through each week of the course for social and technical nodes, Figure 3 focuses on the social nodes only. Our analysis showed that within the social component of the network (Figure 3), the original facilitators (i.e., @gsiemens and @downes) demonstrated a high level of influence within the first week. This level of influence dramatically dropped as the course progressed. Still, both course facilitators remained among top twenty influential nodes by the end of the course, even

though their hub and authority weights decreased more than a half. Several participants (e.g., @profesortbaker, @jaapsoft, and @thbeth) quickly emerged as authorities in the information flow. The hub weights distribution also shows that course participants took on one of the teaching functions – i.e., they became hubs of information flows (Figure 3). Besides the central course node (i.e., @cck11feeds) that pointed to the largest number of authorities, several “emerging” curators and aggregators became important information providers within the network, some very early on (e.g., @profesortbaker, @thbeth, @daisygrisolia, and @jaapsoft) and some a half way through the course (e.g., @web2oeducation). Although a handful of social nodes functioned as both hubs and authorities (Figure 2, Figure 3, Figure 4), some nodes scored high only as authorities (e.g., @downes, @zaidlearn, @jgchesney, @saadat\_m, @gordon\_l, and @gsiemens ). Out of the top twenty authorities that have lower hub weights, the two were original course facilitators, and the others were emerging facilitators, all from the higher education sector and engaged in education research and practice.

Influence over the information flow in the network is exercised through node location in relation to each other. Measurement of the betweenness centrality (Figure 5), revealed those individuals that performed a critical role in brokering information among sub-networks formed in the course (Aggarwal, 2011). Although the course Twitter node (@cck11feeds) maintained high betweenness centrality values throughout the course, betweenness centrality of *emerging facilitators* was higher, and thus, even more significant (e.g., @profesortbaker and @web2oeducation). We also observed an interesting pattern for the nodes who were guest speakers in the course (e.g., @davecomier and @francesbell). They attained temporary attention by being some of the most significant brokers in the network within a few weeks after they presented on a selected topic in the course.

The values of the closeness centrality measures showed that both social and technical nodes – associated with the course and the original facilitators – had the highest proximity to the course participants. Given that closeness centrality measures how distant a node is from all others in the network (Aggarwal, 2011), it seems reasonable that the original course facilitators were among the nodes linked to the greatest number of participants. It also indicates their relative influence in the network, since close distances to most participants indicate that they could reach out to the majority of learners fast.





*Figure 2.* Variation of the authority weights for the top ranked social and technological nodes, over the twelve weeks of the course.

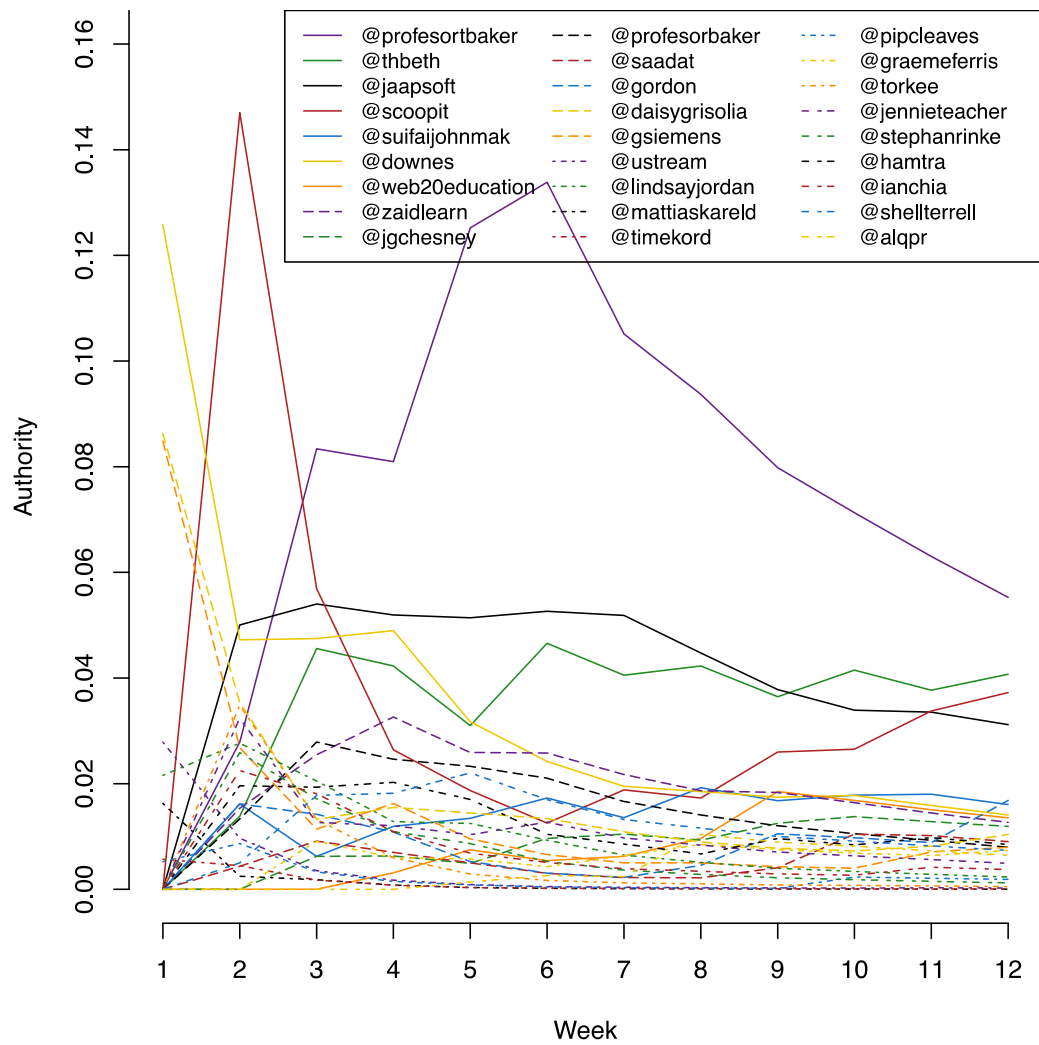


Figure 3. Variation of the authority weights for the top ranked social nodes, over the twelve weeks of the course.

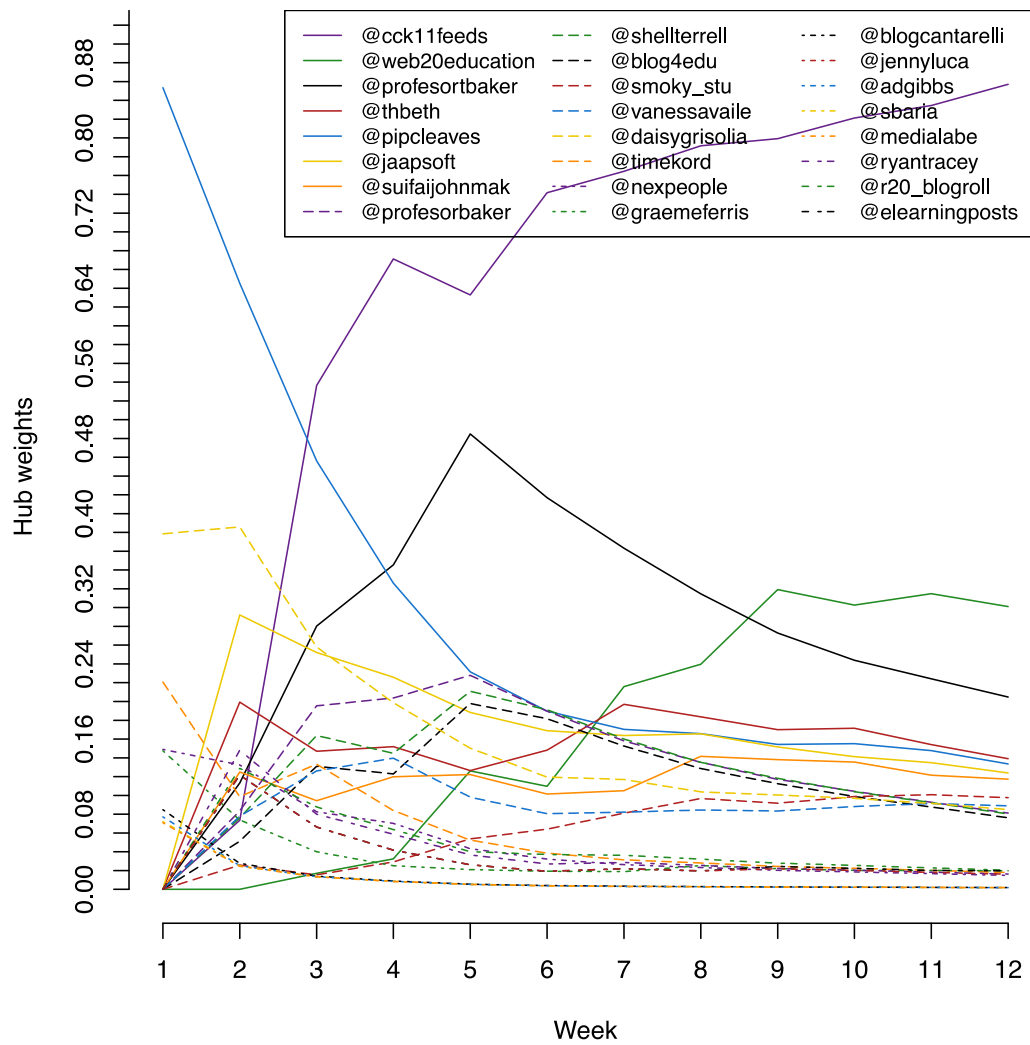


Figure 4. Variation of the hub weights for the top ranked nodes, over the twelve weeks of the course.

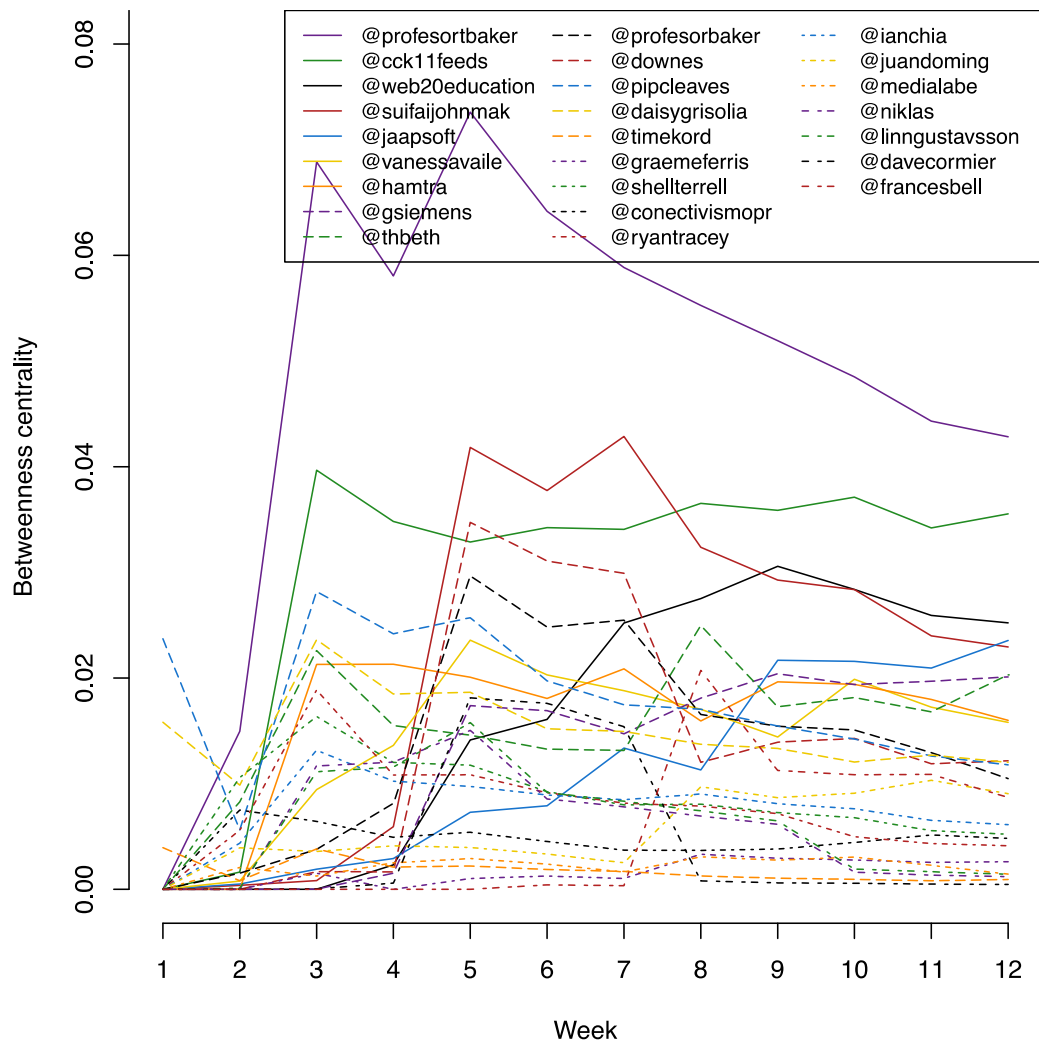


Figure 5. Variation of the betweenness centrality values for the top ranked nodes, over the twelve weeks of the course.

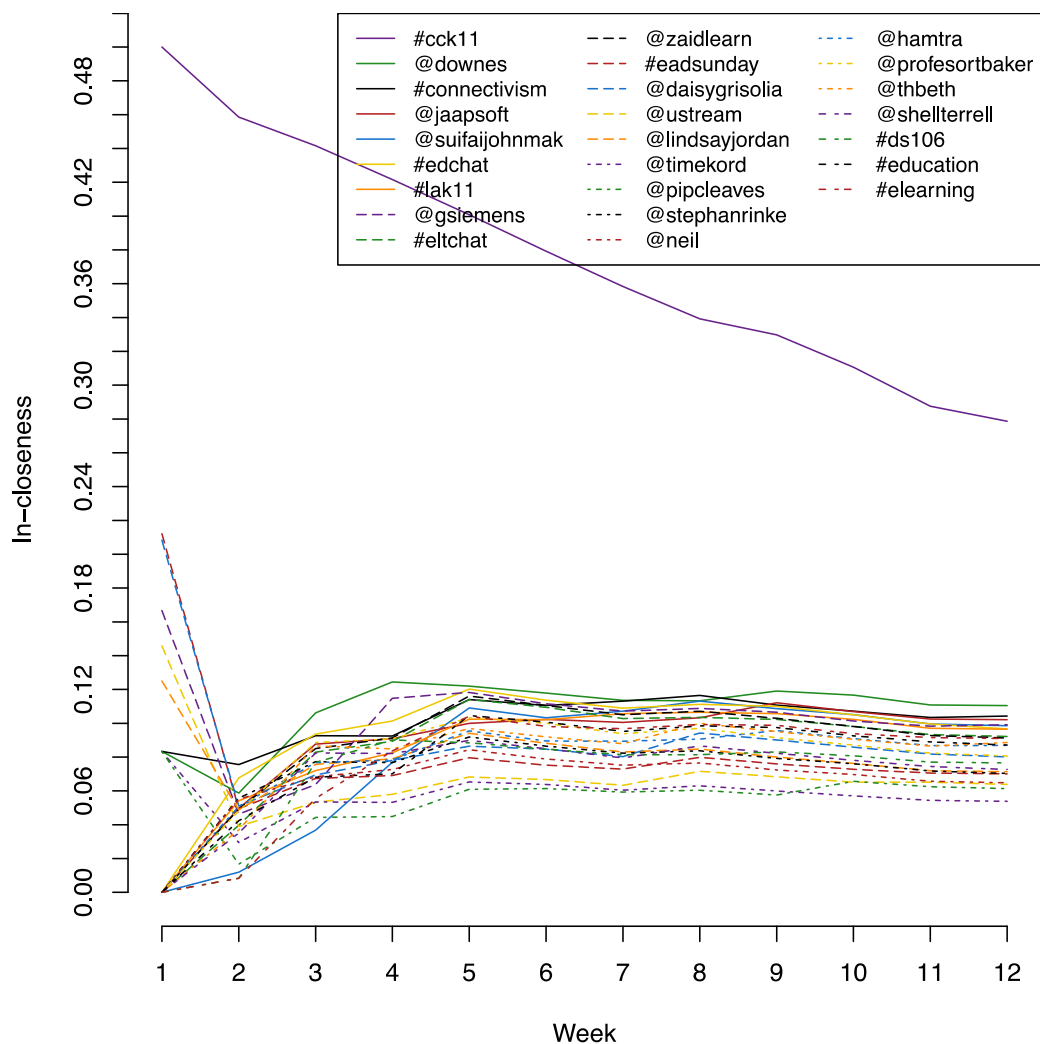


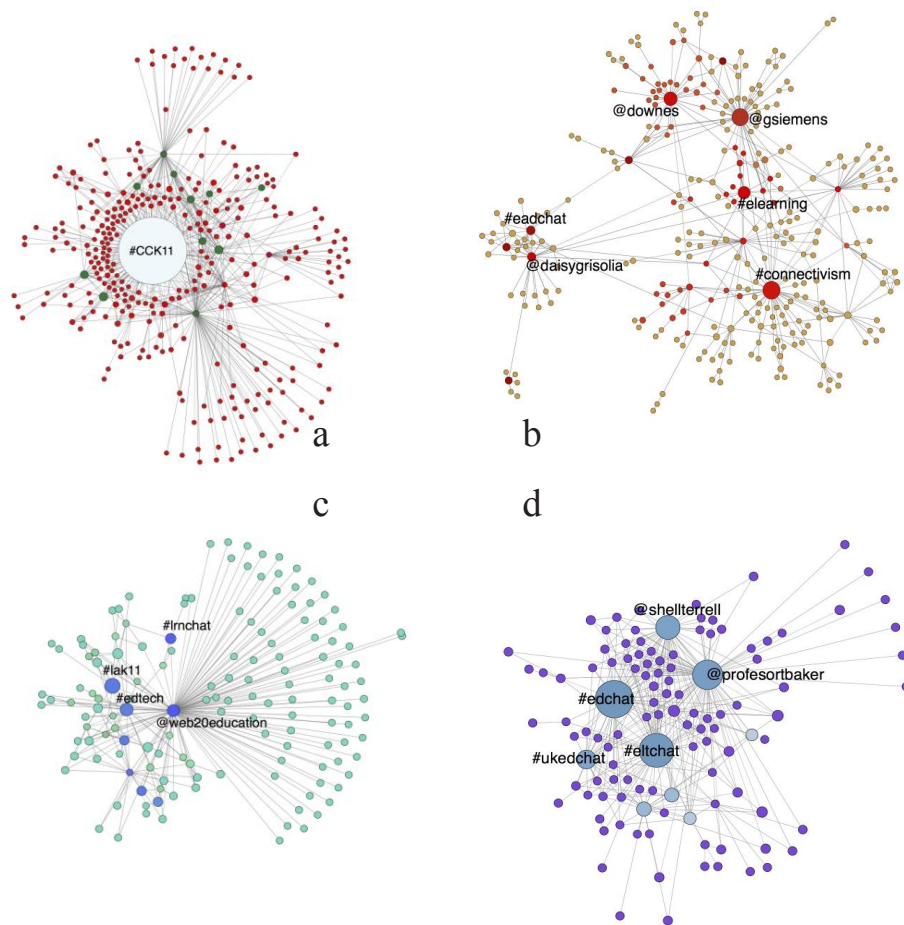
Figure 6. Variation of the input closeness centrality values for the top ranked nodes, over the twelve weeks of the course.

## Formation of Communities

Research question 2 focused on the identification of emerging communities within the broader network structure. A modularity algorithm for detection of communities (Newman, 2006) was performed over a larger connected component resulting in the detection of 19 communities. These observed communities ranged from as large as 26% of the network to as little as 0.3% of the network. The communities were reflected by a shared interest or shared professional background that united the individuals into a community. Figure 7 shows the structures of the four largest

communities. These four communities exemplify a common pattern of having one or two central nodes (sized and coloured by weighted in-degree in Figure 7) that served as the community nuclei. These nuclei occupied central positions in their sub-networks, which indicated their function of the influence over the information flow in their sub-network. From one community to the next, the larger sub-networks were centered around one or more social nodes with high ranks for authority, hubs, or degree, and who were previously identified as influential. These nodes were usually accompanied by technological nodes (i.e., hashtags that were typically created but these influential social nodes) that evolved from a content mark-up to a community identifier.

The largest sub-network revolved around #cck11 (Figure 7a), and included either some of the most active or the most popular nodes (e.g., @vanessavaile, @jaapsoft, and @suifaijohnmak). Interestingly, according to the modularity algorithm original course facilitators were not identified as a part of this sub-network. This means that they were not as closely interconnected with the members of this sub-network, as compared to their connectedness to the nodes of another sub-network. In that sense, this largest sub-network of learners has its own emergent authorities (i.e., @francesbell, @thebeth, @gordon\_l, and @hamtra). The second largest sub-network was the home for both original course facilitators; in this community, @downes and @gsiemens were two magnets with many satellites around them (Figure 7b). Quite a few social nodes around them were researchers well-known in the field of online education (e.g., @jimgroom, @cogdog, @mwell, @ignatia, @davecormier, @gconole, and @etiennewenger). The sub-network that included @gsiemens and @downes also hosted many higher education researchers. Through #elearning and #connectivism, higher education researchers and practitioners from this community reached out to smaller sub-communities of practitioners (Figure 7b). For example, a Brazilian sub-community was formed early in the course and led by @daisygrisolia and around a hashtag #eadchat, a chat about distance education, i.e., “educação a distancia” in Portuguese. The remaining two sub-networks given in Figure 7 (c-d) showed similar dynamics. Figures 7c and 7d depict the cases of @professortbaker with the #eltchat community and @web2oeducation with the #edtech20 community. The network positions of @professortbaker and @web2oeducation have been explained above.



*Figure 7.* Structure for the four exemplary modular sub-networks. Sub-networks are manually separated from each other and the remaining sub-networks of strongly connected component, based on the outputs of modularity algorithm. Networks were manipulated for visualization. A comprises 26%; B =25%; C=12%, D= 9% of the entire course network; node size and distinctive colour size corresponds to the in-degree.

Social network analysis combined with qualitative demographic data demonstrated that these emerging communities were interest-based, and that their development was facilitated via technical nodes (i.e., hashtags) and one or two active social nodes (i.e., course participants). These empirical results reflect the premise of the connectivist philosophy based on the diversity of learners and offered some evidence that the power and control over the information flow were distributed among the network participants who were not original course facilitators (i.e., Stephen Downes and George Siemens).

## Results and Discussion

In the investigated cMOOC, teachers, course participants, and Twitter hashtags all had a role to play in the flow of course discussions. Our analysis confirms that course facilitators preserved a high level of influence over the flow of information in the course as both facilitators maintained influential positions, as shown by their high authority weights, and high betweenness and closeness centralities. These measures represent that course facilitators kept a position of prestige among other influential nodes (authority weights). They also maintained their roles as brokers between disparate parts of the learners' network (betweenness centrality), and therefore, held a level of influence on how fast information could spread around the network (closeness centrality). It should be noted that all SNA measures describing the positions of course facilitators in the network of learners have decreased over the duration of the course.

In relation to the role of course participants in the network of learners, our analysis indicated that over the course progression, a group of nodes developed network positions comparable to those of facilitators. This group of emergent influential nodes included both human participants and hashtags. More specifically, as measures of facilitators' centrality associated with various aspects of influence over communication in the course have decreased, we observed the increase of the same centrality measures describing the positions of some technological and social nodes. This indicates that changes in the network structure occurred (Figure 2-6). By the end of the course, it is the learners and Twitter hashtags that are mostly mentioned (high in-degree) and that produced the highest volume of content (i.e., obtained high out-degree).

Our study also shows that top ten nodes with the highest in-degree were primarily hashtags. This suggests that people were connecting around thematic markers of common interest, referring to them and making them popular. In fact, thematic analysis of the same dataset (Joksimović, Kovanović, et al., 2015) confirms that the learners were more focused on the topics of interest, rather than those suggested by course facilitators, and that those topics emerged quickly in the course, and were maintained by the groups of people that adopted them. Hashtags also achieved high SNA metrics on closeness centrality, indicating that some themes were adopted by an overwhelming majority of learners. Finally, a few hashtags with high authority weights were the thematic markers used by many influential human nodes.

The study findings suggest that both human and technological actors subsumed the teaching functions, and exerted influence over the network. It appears that with time, several interest-based sub-communities emerged. By visualizing the structure of these emerging sub-networks from week-to-week, we observed that some of the influential nodes were instrumental to the formation of these sub-networks. Such course participants as @professorbaker or @web2oeducation exercised sharing activities related to the teaching functions of the course such as curating, aggregating and being persistently present. The nature of their contribution was diverse – from sharing the information about weekly activities and promoting blogs, to giving



their opinion on the topics of interest or challenging new opinions based on topics being discussed. Other learners picked up some of the thematic markers (hashtags) used by these highly prolific participants, and interest-based sub-networks were formed around such hashtags.

Not all individuals maintained equally high metrics on all the SNA measures. That implies the different participants may play slightly different roles in the course: i) hyperactive aggregators that evolve into curators for specific topics and ii) less visible yet influential authorities. The demographic characteristics for these hyperactive users are diverse. Complementary research on ‘super-posters’ in xMOOCs suggests that online hyperactivity may be a natural personality trait (Huang, Dasgupta, Ghosh, Manning, & Sanders, 2014). Future research should investigate the effects of individual differences – such as the big five personality traits (Digman, 1990), epistemic beliefs, personal goals set in a course, metacognition, digital literacy, and familiarity with a particular medium/technology on behaviour within a network. Findings of such research could be used to construct informed instructional interventions that may help individual learners and the network as a whole become more effective in knowledge construction and information sharing. For stronger generalizations about the role of hyperactive network-oriented individuals, it is necessary to conduct further inquiries into distributed MOOCs.

Current study offers an initial peak into how networks of learners are developed in scaled online courses. First and foremost, it is limited to the specific disciplinary nature of the course, and further studies are required to test for generalizability of the findings across a diversity of disciplines adopting a cMOOC design. Secondly, study results only partially represent the full suite of social and technical interactions that were formed during the course. For our analysis we selected only one medium (Twitter) due to its heavy adoption and usage among course participants and therefore, interactions within blogs, synchronous activities, a Facebook group, and other social media were excluded. Finally, CCK11 mirrored the content of its preceding course CCKo8. This duplication of the course offering needs to be investigated in future research, as it is possible that a subset of the participants had pre-existing relationships and established expectations related to the course offering.

The findings reported in this paper offer a number of research and practical implications. Firstly, information sharing within cMOOCs must account for both the role of technological agents as well as social (i.e., human) agents. Modeling the network formed around a cMOOC from the socio-technical perspective, we were able to observe the importance of technology, and its influence on shaping discussions within the cMOOC under investigation. The fact that hashtags were the most popular nodes (based on weighted out-degree measures) and that the role they played in the community development and hub/authority promotion indicates that they should be observed in the analysis as equally important as the social nodes comprising the overall network structure. Technological nodes showed a significant influence on the choices made and content of interactions among the social nodes. As the technological nodes did not fulfill any of the community-related functions on their own, the community formation was established through

the choices and actions of the social nodes. Still, their choices were influenced by the affordances of the technology used for information sharing and social interaction (e.g., search by hashtags).

The application of social network analysis and the inclusion of multiple technologies pose numerous methodological and practical challenges. For example, should a network be constructed based on the interaction of all these different sources, and if so, should the links from different media be weighted differently? Practically, the integration of users identified from different social media can be a challenge and can pose a threat to the validity of such an approach. Alternatively, is it more suitable to have separate social networks for each medium of interaction and compare patterns of networks among such networks? It is likely that in some cases both approaches (i.e., single joined and multiple separate networks) will be used depending on the types of questions asked in the studies and the particular narrative to be explored. In that process, understanding of the previous learners' experiences with learning in similar settings and technologies used can be essential. For example, in a course that attracts many educational technologists, the use of social media such as Twitter can play the critical role; in other cases (e.g., computing), some other media can be preferred by the course participants (e.g., discussion boards). Theoretically, socio-technical networks are poised to change teaching dynamics from the wide-spread model of command and control of the learning process to a more embedded networked facilitation (Siemens, 2010). However, this transformation does not simply arise as a result of course design. Transformation will only happen when certain pedagogical choices are embraced and promoted. In this regard, a combination of thematic tagging (through hashtags), searching by tags, and aggregation emerges as a pedagogical technique that allows for more democratic but manageable discussions. This approach however is closely intertwined with the attributes of the particular technologies used in courses. In our study, the role of hashtags in the community creation was apparent. The importance of hashtags shows how a simple mechanism of thematic tagging allows for creating a network within which learners can easily access information and even enable course learners to become the most influential nodes in the information flow (i.e., emerge as facilitators for specific communities).

The significance of hashtags for influencing information flows and community formation can be an important lesson for those who strive to build software that makes centralized discussion forums more learner-centered. Centralized forums could integrate simple features to cater for tagged discussions, and facilitators can adopt support technologies for collecting emerging themes in summaries (similar to gRSShopper). The aggregation of themes provides a social component that may assist learners in forming communities around topics of interest. Such technologies can offer personalized information for each learner by matching information aggregated with the learners' needs and interests. Moreover, discussion forums can also become more fluid by allowing for an easy integration of different social media into discussion forums as done in Elgg<sup>6</sup>, an open social networking software. For example, Thoms & Eryilmaz (2014)

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<sup>6</sup> <http://elgg.org/>

compared the effects of asynchronous online discussions among different groups of students within the same course where the instructional design and content was identical and the only difference was that some groups used Elgg and other groups used a conventional learning management system for asynchronous online discussions. In spite of the instructional equivalency, the groups that used Elgg exhibited a significantly higher academic achievement, student retention learning satisfaction, and the amount of social interactions over the groups that used the conventional learning management. Similar studies are necessary in the context of MOOC research to investigate the effects of the use of different technologies on the roles of original and emerging facilitators in the control of information flow and community formation.

### **Ethical Considerations**

The authors would like to state that there was no conflict of interest involved in the reported study. Datasets were established from information collected in the public domain. Such data collection is exempt from institutional clearance since the information is publicly accessible and there is no reasonable expectation of privacy (Canadian Institutes of Health Research, Natural Sciences and Engineering Research Council of Canada, & Social Sciences and Humanities Research Council of Canada, 2010, p. 17). The research was guided by the Recommendations from the Association of Internet Research Working committee (Ess & the AoIR ethics working committee, 2002; Makrham & Buchanan, 2012). All analysed datasets are stored in a secure password-protected personal repository, and the second author should be contacted for further inquiries regarding access to the data.

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### 4.3 Publication: Exploring Development of Social Capital in a cMOOC Through Language and Discourse

The following section includes the copy that was submitted for the second round of review:

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# Exploring Development of Social Capital In a cMOOC Through Language and Discourse

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## ABSTRACT

Connectivist pedagogies are geared towards building a network of learners that actively employ technologies to establish interpersonal connections in open online settings. In this context, as course participants increasingly establish interpersonal relationships among peers they have greater opportunity to draw on and leverage the latent social capital that resides in such a distributed learning environment. However, to date there have been a limited number of studies exploring how learners build their social capital in open large-scale courses. To inform the facilitation of learner networks in open online settings and beyond, this study analyzed factors associated with how learners accumulate social capital in the form of learner connections over time. The study was conducted in two massive open online course offerings (Connectivism and Connective Knowledge) that were designed on the principles of connectivist pedagogy and that made use of data about social interaction from Twitter, blogs, and Facebook. For this purpose, linear mixed modelling was used to understand the associations between learner social capital, linguistic and discourse patterns, media used for interaction, as well as the time in the course when interaction took place. The results highlight the association between the language used by the learners and the creation of ties between them. Analyses on the accumulation of connections over time have implications for the pedagogical choices that would be expected to help learners leverage access to potential social capital in a networked context.

**Keywords:** MOOC, Social capital, Social network analysis, Linguistics, Discourse, Connectivism

The importance of peer interactions for the learning process has been a consistent narrative in all forms of education. Research in the distance courses, online and blended courses, and more recently in open scaled courses in distributed environments have all stressed the need for developing peer to peer interactions to promote student learning and achievement of course goals (Bernard et al., 2009; Borokhovski, Tamim, Bernard, Abrami, & Sokolovskaya, 2012; Joksimović, Gašević, Loughin, Kovanović, & Hatala, 2015). As a new educational provision within online education, Massive Open Online Courses (MOOCs) have triggered heated media and academic discussions about a range of issues. For instance, there has been much debate over the validity of learning in such an open scaled environment as well as the challenges in establishing online interpersonal interactions at scale without losing a more socially oriented learning model (Gašević, Kovanović, Joksimović, & Siemens, 2014; Reich, 2015; Reich, Stewart, Mavon, & Tingley, 2016). The technical transition to learning at scale resulted in a need for existing pedagogical models to move beyond mere transmission of teacher-produced content. The capacity to deliver online course to the masses requires the ability to scale learner centric pedagogies in new ways that enable the production of social interactions among thousands of learners (Stewart, 2013).

The first MOOCs – today commonly known as connectivist MOOCs (cMOOCs) – emerged as an innovative solution to scaling learner interactions. They were designed as an alternative to the more conventional online education practices that delivered content via a single (centralized) platform. That is, conventional online education is, and remains, constrained in the number of opportunities readily available to learners to connect outside of teacher-controlled systems. In addressing this limitation, facilitators of the first cMOOCs scaled learner interactions by using diverse media for sharing, aggregating, and connecting information. In cMOOCs, learners were encouraged to interact with each other on the basis of personal goals and common interests (Mcauley, Stewart, Siemens, & Cormier, 2010). Establishing social ties with other learners mediated by technology was thought to be integral to the learning process (Anh, Butler, & Alam, 2013; Knox, 2014).

The connectivist model of learning (Siemens, 2005) assumes there is an untapped abundance of information that resides in distributed networks. The connectivist model perceives technology as distributed, courses less structured and without formal assessment, while the teaching is focused on instructional design and learner facilitation (Siemens, 2005). Knowledge was approached as distributed among the network of learners, whereas learning was viewed as the development and maintenance of networks of information, resources and contacts (Anderson & Dron, 2011). The main premise for learning in a connectivist setting is that learners form connections based on shared interests, at the same

time learners are invited to explore various topics, to decide what to learn, and to choose communication media that are best suited to their needs (Mcauley et al., 2010).

Although online educators and researchers have explored and critiqued the theoretical grounds of connectivist courses (Bell, 2010), there remains a paucity of empirical research providing evidence of how such learning would unfold in the pedagogical context of connectivism. Empirical insights into learning in cMOOCs have been limited due to the technical difficulty of collecting cMOOC interactions distributed over the Internet. Consequently, the majority of cMOOC research has relied on self-report mechanisms, i.e. course evaluations, participant surveys and interviews (Fini, 2009; Kop, 2011; Kop, Sui, & Mak, 2011; Milligan, Littlejohn, & Margaryan, 2013). Observational evidence, however, should provide a more scalable approach in studying learning in connectivist settings.

In our prior work, we collected a dataset of two connectivist courses to gain insight into how learning unfolds in the pedagogical context of connectivism. For example, Skrypnik, Joksimović, Kovanović, Gašević, and Dawson (2015) utilized observational data to capture the transition from course facilitation as primarily instructor-driven to a more learner-driven and self-organized model - the central pedagogical characteristic of cMOOCs (Siemens, 2010). The results demonstrated that as the number and density of students' connections in a network increased in the course there was an associated transition in power and control from facilitator to student. In essence, the growing network structure resulted in, some participants securing a network position that gave them "power and control" over the information flow in the course that was on par with the original course facilitators (teachers).

The current study further contributes to our understanding of learning in connectivist settings. It investigates factors associated with a successful learning experience from a connectivist perspective. Within the connectivist pedagogy, learning outcomes are not pre-defined by a facilitator. The creation of network links, or physically establishing connections from learner to learner, is considered learning in the sense that it enables faster access to new information and resources (Siemens, 2005). Connecting to another person opens access to different kinds of benefits, unavailable if the connection is not made. In this sense, a learner's position in the network represents the potential to learn from the network, due to their level of access to informational resources, personal support and/or professional opportunities that are embedded within the entire course network.

A learner's position in a social network is also reflective of the available social capital a learner can draw upon to support their learning endeavors (Haythornthwaite & De Laat, 2012). Individual social positioning at varying time points in a course can indicate the level of access to social capital and how this can influence successful participation in an open course. Such an approach is theoretically rooted within the network theory of social capital by Lin (Lin, Cook, & Burt, 2001). According to Lin, social

capital is defined as a personal investment into building network connections (Lin, Cook, et al., 2001) that can be accessed to aid achievement of individual goals. Access to social capital is well captured and typically operationalized through the measures of network centrality as commonly used in social network analysis (Lin, Cook, et al., 2001; Lin, Fu, & Hsung, 2001) (SNA). Network measures incorporate both the number of connections made, and opportunities and limitations available to an individual due to the positions they occupy within a social network (Burt, 2000).

This study explored the factors related to the development of social capital of learners in the three main social media software (i.e., Twitter, Facebook, and blogs) used in two connectivist MOOCs (i.e., CCK11 and CCK12). Social capital was measured through centrality measures derived from social network analysis. We used linear mixed effects modeling to investigate whether the development of social capital is associated with how learners utilize language for communication, as measured through different linguistic and discourse features (Graesser, Mcnamara, & Kulikowich, 2011). To account for contextual factors that may mediate the association between learner discourse and social capital, linear mixed models included (a) the effects of social media through which interactions occurred, (b) the overall amount of learner activity and (c) the time in the course when interactions took place. The paper builds on the previous research presented in the Joksimović and colleagues (2015) study to offer a comprehensive analysis of factors that influence the development of social capital in online courses facilitated by social media.

## 2. Theoretical Background

### 2.1 Social capital

Contemporary definitions of social capital can vary significantly. Despite the diversity of interpretations there is general agreement that social capital represents an investment in social relations for some future expected returns (Lin, 1999). Given the context of our research (i.e., studying learning in distributed online/networked settings), we adopted Lin's (2008) definition of social capital. Observed through the lens of three families of social concepts discussed by Paldam (2000), Lin's definition stems from the *network* family, implicitly building on the concept of *network payoff* that conceptualize social capital as being equal to the amount of benefits *one* can draw on his network. In essence, Lin's (2008) definition, interprets social capital from the perspective of individual network actors as they create new connections that enable them to access the resources embedded in the broader network structure. In contrast Bourdieu (1986) and Putnam (1993) for example, view social capital at a group-level (e.g., Bourdieu, 1986; Coleman, 1988; Putnam, 1993). This perspective privileges strong ties that are associated with *collective assets* (Williams & Durrance, 2008), such as solidarity, trust, reciprocity, and

norms, to establish a longer term membership developed through network cohesion.

Social networking sites enable for the creation of both weak and strong ties. In his seminal work, Granovetter (1973) distinguished between *strong* (e.g., friends, family) and *weak* (e.g., acquaintances) social ties and showed evidence for the importance of weak social ties on the access to novel information resources. Early work on online communities hypothesized that the Internet, besides being used for maintaining strong social ties, also affords cost and time effective ways of maintaining weak social ties that can be potentially used for informational resources and/or access to opportunities (Liou, Chih, Hsu, & Huang, 2015; Yoo, Choi, Choi, & Rho, 2014). A recent review of evidence connecting social networking platforms (e.g. Twitter, Facebook, and various blogging platforms) with social capital concluded that social network sites are well suited for development, accumulation, and conversion of social capital, i.e., mobilization of social capital for a specific return (Ellison & Vitak, 2015). Furthermore, it has been suggested (Ellison, Wohn, Khan, & Fewins-Bliss, 2012) that social networking sites enable the creation of weak or strong ties from activated latent ties, i.e. the ties that are “technically possible but not activated socially” (Haythornthwaite, 2005, p.137). In the context of cMOOCs and networks of learners, it is the activation of latent ties that affords an opportunity to leverage new information and resources in order to achieve desired learning gains evolving from the relationships with peers.

In building on Lin’s definition, Gaag & Snijders (2003) proposed that measuring social capital should be limited to the access to resources, without accounting for the actual *use* of social ties. Gaag & Snijders (2003) argued that measuring social capital beyond structural access requires accounting for wider contexts beyond those that can be measured. By applying SNA at the level of network actors, the individual access to potential resources can be captured through SNA metrics (Borgatti, Jones, & Everett, 1998). Borgatti and colleagues reviewed network metrics and their hypothetical association with social capital. For example, an individual’s degree, i.e. the number of connections, is theorized as positively related to social capital as individual gain; the more people an individual is connected to, the higher the likelihood that one of these connections will have potentially necessary information. In addition to degree centrality, in this study we adopted eigenvalue, betweenness and closeness centrality. These measures are commonly used indicators that can provide a more in-depth, multi-dimensional assessment of the available social capital (Borgatti et al., 1998).

## *2.2 Contexts for social capital development*

Contextual factors influence the way learners gain access to the available pool of social capital. For instance, students exercise different degrees of activity, convey information in different linguistic styles, and apply media that afford differing modes of interaction. Similarly, the time in the course when interactions take place is potentially important. All these contextual factors may be correlated with

students developing and mobilizing their perceived social capital. These contextual factors are frequently observed across various educational courses. In this study, *learner activity*, *time of course*, *language* and chosen *social media* are the considered contextual factors in the analysis of how learners develop access to social capital in a network.

**Language and discourse.** Language is a primary means for expressing and exchanging content through a network. It is through language that participants are able to build connections and define social ties with other actors. With regard to analytical approaches, there has been extensive knowledge gleaned from manual content analyses of learners' discourse during educational interactions. For instance, the early research of Bernstein (1971) highlighted that individuals with more complex social networks tend to demonstrate more formal and elaborated speech forms than those with more simple and densely connected personal networks. Milroy and Margrain (1980) reported that the variety of language in use is dependent on the density of the social network and the multiplexity of the ties. According to Granovetter (1973), the intensity of ties established between actors affords an opportunity to track the linguistic phenomenon of code-switching, whereby speakers change conversational styles as they converse with interlocutors from the different parts of their sub-networks. These earlier studies illustrate the relationship between social ties and language. However, the manual content analysis methods used in those studies are no longer a viable option with the increasing scale of educational data. Consequently, researchers have been incorporating automated linguistic analysis that range from shallow level word counts to deeper level discourse analysis.

To extend analysis of learning-related phenomena beyond word count measures, one needs to conduct a deeper level discourse analysis with sophisticated natural language processing techniques, such as syntactic parsing and cohesion computation. For example, Dowell, Cade, Tausczik, Pennebaker, and Graesser (2014) explored the extent to which discourse features predicted student performance during computer-mediated collaborative learning interactions in groups of 4 students. Their results indicated that students who generated language with deeper cohesion and more complicated syntactic structures had higher performance scores on tests. Dowell and colleagues (2015) used a similar methodological design in their investigation of student performance in a MOOC. Specifically, they explored the extent to which characteristics of discourse diagnostically reveals learners' performance and social position in a MOOC. Their results for performance mirrored the pattern that was observed for learning in the computer-mediated collaborative learning study (Dowell et al., 2015). Specifically, students who performed significantly better engaged in more expository style discourse, with higher referential and deep level cohesion, more abstract language, and more simple syntactic structures (Graesser, McNamara, & Kulikowich, 2011). However, linguistic profiles of the centrally positioned learners differed from the high performers. Learners with a more significant and central position in their

social network generated a more narrative discourse style with less cohesion among ideas, as well as more simple syntactic structures and abstract words (Dowell et al., 2015). Based on these findings, the linguistic characteristics of learners may provide a promising approach for understanding the factors that lead to the formation of social ties among a group of learners.

In the current research we adopt a multilevel theoretical approach to the analysis of language and discourse. Psychological models of discourse comprehension and learning, such as the construction-integration, constructionist, and indexical-embodiment models, lend themselves nicely to the exploration of learning related phenomena in computer-mediated educational environments. These psychological frameworks have identified the representations, structures, strategies, and processes at multiple levels of discourse (Graesser & McNamara, 2011; Kintsch, 1998; Snow, 2002). Five levels have frequently been identified in these frameworks: (1) words, (2) syntax, (3) the explicit textbase, (4) the situation model (sometimes called the mental model), and (5) the discourse genre and rhetorical structure (the type of discourse and its composition). The computational linguistic facility used in the current study, Coh-Metrix (described more in the methods), allows us to capture these main levels of discourse. In the learning context, learners can experience communication misalignments and comprehension breakdowns at different levels. Such breakdowns and misalignments have important implications for the learning process.

**Social media.** The social media (Twitter, Facebook, Blog) used by the learners in a course is also an important factor influencing interactions. Different social networking software have been known to impact the flow of information and community formation (Gruzd, Wellman, & Takhteyev, 2011). For example, Backstrom, Huttenlocher, Kleinberg, and Lan (2006) reported that community formation in large social networks depends on the structure of the underlying network. More precisely, the growth of communities does not depend on the relationships that an individual has within a network, but rather on the type and strength of these relationships. The use of media has also been shown to be related to the depth of ties connecting communicators (Haythornthwaite, 2002), where more weakly tied communicators rely on organizationally established means for exchanging information. Finally, Androutsopoulos (2006) has argued that the studies focusing on the diversity of language use in computer mediated communication, over time have shifted from “medium-related to user-related patterns of language use” (p.421). This suggests that different communication media (e.g., e-mail, blogs and chat) should be observed in terms of technological affordances that constrain discourse styles within the social media (Androutsopoulos, 2006).

**Time.** Previous studies on online learning have emphasized the relevance of the temporal dimension in the analysis of learning-related processes (Barbera & Reimann, 2014; Kovanović et al., 2015; Reimann, 2009). Integrating longitudinal data into statistical analyses can provide insights into micro-



processes, developmental sequences, phases, and time scale durations (Chiu et al. in Barbera & Reimann, 2014). For example, the development of social presence in the community of inquiry framework has been connected with time (Akyol & Garrison, 2008), showing that, as the course progresses, students undergo a transitional phase from social presence to cognitive presence. This process is in line with the mainstream premise of small groups research that social structures evolve sequentially (Arrow, Poole, Henry, Wheelan, & Moreland, 2004). As another example, missing the early time for peer discussion may impact performance and drop-out, as demonstrated in face-to-face settings (Vaquero & Cebrian, 2013) as well as online interaction in MOOC research (Rosé et al., 2014). Due to these important implications, we measured the sequence of weeks in the courses under investigation.

**Learner activity.** The assumption that activeness of an individual reflects interest and motivation is often used in xMOOC studies, where trace data on course resources is correlated with student perseverance or academic achievement (DeBoer & Breslow, 2014). “Activeness” is also relevant to understanding how social capital is developed and accumulated (Skrypnyk et al., 2015). In their analysis of a network emerging from a cMOOC, Skrypnyk and colleagues (2015), identified a group of so-called prolific learners, characterized by their high out-degree. This group of learners’ author text more frequently compared to their peers. Similarly, a group of participants, called super-posters (Huang, Dasgupta, Ghosh, Manning, & Sanders, 2014) have been identified through their extensive participation in xMOOC forums. In both cases, it is not necessarily the content of the messages, but the sheer volume and frequency of the contributions that make these learners more “visible”. Moreover, in the context of the cMOOC, these prolific learners over time tend to attract more people to their discussions and are often instrumental to community formation. Therefore, this study measured the amount of learner contributions as one of the factors impacting the development of social capital.

### 3. Research Questions

The goal of the current research is to understand the influence of a broad suite of contextual factors in the development of social capital in a connectivist MOOC (cMOOC). Specifically, we investigate the role of language, media, time, and learners’ activeness on centrality.

Communication is a primary means of exchanging information in emerging educational environments, like MOOCs, and as such it plays a critical and complex role (Dowell et al., 2015). The current study approaches the analysis of linguistic features used by MOOC participants and participants’ overall engagement as a method to gain insights regarding the quality of ties formed between the learners. Additionally, because the relationship between learners occurs over time, it is difficult, if not impossible to consider learners’ social position without time playing a role. Therefore, we explored

temporal changes in learners' discourse and the position within the network as the course progresses. Finally, social media applications vary in their affordances for the use of language. Linguists do not approach Internet language as a fixed discourse register, despite its unique features (Crystal, 2001), but rather treat it as “resources that particular users might draw on in the construction of discourse styles in particular contexts” (Androutsopoulos, 2006, p.421). In other words, different types of media are seen as varying contexts for users to engage with. Different media types also influence the use of language and thereby help shape various discourse genres (Androutsopoulos, 2011).

Drawing on this theoretical and empirical background, we explored the following three research questions:

**RQ1.** How is the language used by cMOOC participants associated with the positions that define an individual's access to the social capital in the network of learners?

**RQ2:** What is the role of different communication media on the development of the social capital?

**RQ3.** What are the temporal dynamics of social capital in a cMOOC?

## **4. Method**

### *4.1 Data*

This study examined blog, Twitter and Facebook posts from the 2011 and 2012 editions of the Connectivism and Connective Knowledge (CCK) course. These courses were designed as open online courses aiming to explore the ideas of connectivism and connective knowledge, and to examine the application of the connectivist framework in theories of teaching and learning. Both course offerings were facilitated over a 12-week period: CCK11 was delivered from January 17<sup>th</sup>, 2011 to April 11<sup>th</sup>, 2011, while CCK12 took place between January 23<sup>rd</sup>, 2012 and April 11<sup>th</sup>, 2012. Course resources were delivered using gRSShopper<sup>1</sup>, while live sessions were carried out using Elluminate<sup>2</sup>. Given the specific (connectivist) nature of the course, students were not obliged to use any particular platform and/or media to interact with other students. However, course facilitators suggested students do share their insights and resources about the course content using technologies such as blogs, Facebook, Twitter or other discussion groups and social media. Finally, gRSShopper was used to provide students with a daily newsletter that aggregated content produced by the course participants on Twitter and their personal blogs. This method allowed automatic gathering of links to blog posts and copies of tweets. Facebook

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<sup>1</sup> <http://cck11.mooc.ca/>, and <http://cck12.mooc.ca/>

<sup>2</sup> <https://sas.illuminate.com>

data were collected using Facebook API<sup>3</sup> in order to retrieve communication between course participants.

The data are publicly available from the respective course sites. Moreover, the collected data are available upon request, stored in the JSON format with the following information:

- **Twitter:** authors' name, date/time created, media attached (e.g., photo, video, web page), mentions, and hashtags;
- **Blogs:** authors' name, date created, title, URL, as well as posted comments with information about comment's author and date/time created;
- **Facebook:** besides basic information about authors' name and date/time created, Facebook posts contain all the information specified in API documentation.

To support the analysis of content created in multiple languages, messages posted in languages other than English were translated using Microsoft Translation API<sup>4</sup> (around 5% of messages were translated). The total numbers of posts produced in CCK11 ( $N_{\text{post11}}=5711$ ,  $M=2.59$ ,  $SD=4.47$ ) and CCK12 ( $N_{\text{post12}}=2951$ ,  $M=3.41$ ,  $SD=9.06$ ) differed, with CCK12 having fewer active students ( $N_{\text{cck11}}=997$ ,  $N_{\text{cck12}}=429$ )<sup>5</sup>. However, despite a smaller cohort the participants demonstrated a higher average activity. The difference in activity can also be seen through the comparison of the volume of posts made on Facebook ( $N_{\text{post11f}}=1755$ ,  $N_{\text{post12f}}=61$ ) and blogs ( $N_{\text{post11b}}=1473$ ,  $N_{\text{post12b}}=624$ ) in both courses. Twitter-mediated communication sustained similar high levels of activity for both courses ( $N_{\text{post11t}}=2483$ ,  $N_{\text{post12t}}=2266$ ).

#### 4.2 Analyses

In order to address the research questions, SNA was first conducted to calculate centrality measures defining the structural positions of individual learners in the networks for each course. Next, algorithms behind the Coh-Metrix principal components (described later) were applied to calculate measures representing linguistic and discourse features of individual learners' interactions. All measures were calculated on a week-to-week basis in order to address the third research question. Finally, statistical analyses were performed to identify whether the linguistic features of learners' interactions, social media used, temporal dimension, and learners' activities were associated with their structural positions. A linear mixed effect model was conducted statistically assess the contributions of the alternative media, time, and learner activeness as well as the variance attributable to differences among individuals.

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<sup>3</sup> <https://developers.facebook.com>

<sup>4</sup> <http://msdn.microsoft.com/en-us/library/dd576287.aspx>

<sup>5</sup> Number of students for courses under study, represents the number of active students that participated in communication using three social media platforms analyzed.

**Social Network Analysis.** Twitter, blogs and Facebook were the most widely used media for interacting in each course. Therefore, 72 undirected weighted graphs were constructed to represent interactions independently mediated by these three technologies for each week of each course. That is, each of the two courses included three networks that were formed from the different media types. These networks were constructed 12 times (one per week) for each medium within the course. *Twitter graphs* included all authors and mentions as nodes of the network, whereas the edges between them were created if an author or an account were tagged within the tweet. For example, if a course participant @Learner1 mentioned @Learner2 and @Learner3 in a tweet, then the course Twitter network would contain @Learner1, @Learner2, and @Learner3 with the following edges: @Learner1 – @Learner2, and @Learner1 – @Learner3. Network graphs representing interactions in blogs and on Facebook included authors of the posts, i.e., blog owners or Facebook post initiators, as well as authors of comments to either of these. If a learner A1 created a blog or Facebook post, and then learners B1 and C1 added comments to that post, then the corresponding network would contain nodes A1, B1, and C1 with the following edges: A1-B1, and A1-C1. Graphs for each week included authors who posted and/or commented within the given week only.

Principles and methods of graph theory have been commonly used to assess the values of different network positions (Wasserman & Faust, 1994). Of particular importance is the notion of centrality that is commonly used to capture the importance of an individual node in the network (Wasserman & Faust, 1994). Therefore, the following well-established SNA measures (Freeman, 1978; Wasserman & Faust, 1994) were calculated for each learner in all network graphs:

- **Degree Centrality** – the number of edges a node has in a network;
- **Eigenvalue Centrality** – the measure of influence of a given node;
- **Closeness Centrality** – the distance of an individual node in the network from all the other nodes;
- **Betweenness Centrality** – the number of shortest paths between any two nodes that pass via a given node.

The social network variables were analyzed using *igraph 0.7.1* (Csardi & Nepusz, 2006), a comprehensive R software package for complex social network analysis research.

**Linguistic analysis.** For linguistic analysis, the texts produced by individual learners via different media were parsed in weekly chunks. For example, all text produced by Learner 1 on Twitter in week 1 of CCK11 was treated as one unit, while all text produced by the same learner on Facebook in week 1 of CCK11 was treated as another unit. To analyze discourse patterns on multiple levels, we used Coh-Metrix, arguably the most comprehensive automated textual assessment tool currently available on the Web (Graesser et al., 2011; McNamara, Graesser, McCarthy, & Cai, 2014).

Coh-Metrix is a computational linguistics facility that analyzes higher-level features of language and discourse (Graesser et al., 2011; McNamara et al., 2014). Coh-Metrix has been used to analyze texts in K-12 for the Common Core standards and states throughout the U.S. (Arthur C Graesser et al., 2014; Nelson, Perfetti, Liben, & Liben, 2012). More than 50 published studies have demonstrated that Coh-Metrix indices can be used to detect subtle differences in text and discourse (McNamara et al., 2014). The Coh-Metrix website<sup>6</sup> provides over 100 measures at multiple levels, including genre, cohesion, syntax, words and other characteristics of language and discourse. Coh-Metrix also has measures of linguistic complexity, characteristics of words, and readability scores. There was a need to reduce the large number of measures provided by Coh-Metrix into a more manageable size. This was achieved in a study that examined 53 Coh-Metrix measures for 37,520 texts in the TASA (Touchstone Applied Science Association) corpus, which represents what typical high school students have read throughout their lifetime (Graesser et al., 2011). A principal components analysis was conducted on the corpus, yielding eight components that explained an impressive 67.3% of the variability among texts; the top five components explained over 50% of the variance. Importantly, the components aligned with the language-discourse levels previously proposed in multilevel theoretical frameworks of cognition and comprehension (Graesser & McNamara, 2011; Kintsch, 1998; Perfetti, 1999; Snow, 2002) and thus are suitable for investigating trends in learning-oriented conversations.

TABLE 1  
THE SUMMARY STATISTICS OF THE LINGUISTIC MEASURES (Z-SCORES) USED IN THE STUDY

Name	Average	St. Dev.	Min	Max	Median
Narrativity	-0.920	1.672	-7.410	4.660	-0.580
Deep Cohesion	-0.099	1.394	-4.730	26.560	-0.180
Ref. Cohesion	-0.747	3.482	-17.100	10.100	-0.750
Syn. Simplicity	-0.230	3.068	-5.260	11.330	-0.870
Word Concreteness	-1.423	2.337	-7.600	14.580	-1.320

In this study, the following five principal components of Coh-Metrix were calculated for each of the units (Table 1):

- **Narrativity.** The extent to which the text is in the narrative genre, which conveys a story, a procedure, or a sequence of episodes of actions and events with animate beings. At the other end of the continuum are more informational texts.

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<sup>6</sup> [www.cohmetrix.com](http://www.cohmetrix.com)

- **Deep Cohesion.** The extent to which the ideas in the text are cohesively connected at a deeper conceptual level that signifies causality or intentionality.
- **Referential Cohesion.** The extent to which explicit words and ideas in the text are connected with each other as the text unfolds.
- **Syntactic Simplicity.** Sentences with few words and simple, familiar syntactic structures. Polar opposite are structurally embedded sentences that require the reader to hold many words and ideas in their working memory.
- **Word Concreteness.** The extent to which content words are concrete, meaningful, and evoke mental images as opposed to abstract words.

**Statistical analysis.** A mixed-effects modeling approach was adopted for all analyses due to the repeated measurements and nested structure of the data. Specifically, learners were nested within the courses in our analyses. Mixed-effects modeling is a recommended method for analyzing such datasets (Pineiro & Bates, 2000). Mixed-effects models include a combination of fixed and random effects and can be used to assess the influence of the fixed effects on dependent variables after accounting for any extraneous random effects. Fixed effects correspond to the numerical or categorical variables that are of primary interest and represent fixed, repeatable levels among which comparisons are to be made. Random effects are categorical variables that represent variability among subjects, a random selection from a larger population to which the results can be extended.

A mixed-effects modeling approach yields a stringent test of the contributions of language, media, time, and learners' activeness on centrality by controlling for the variance associated with individual students and course differences. More specifically, this approach allows for testing our primary questions of interest, namely the correlation contributions of language characteristics, the media used, and time on social capital (measured via the four centrality measures) in an online educational environment. Therefore, four different linear mixed-effects models were constructed, one for each of the centrality measures. Within each model one centrality measure (i.e., degree, eigenvalue, betweenness, and closeness) was considered as a dependent variable. The independent fixed effect variables included five Coh-Metrix *principal components*, *media* (Twitter, Facebook, and Blogs), and *week sequence* to assess any potential temporal influences on linguistic properties. The *count of posts* was incorporated to take into account the relative activeness of course participants. To address the impact of individual variance within a model, learners within a course and a course were treated as random effects.

Several steps were taken in relation to the choice of mixed effects regression models. For each of the dependent variables we constructed three models (Table 3): (a) a *null model* with the random effect only (*student within a course*), (b) a *fixed effects model* that included the random effect, as well as Coh-

Metrix principal components, media (Twitter, Facebook, and Blogs), week, and post count as fixed effects, and (c) a *full model* that introduced *course random slope* to account for variability at the course level. A comparison of the null model with the *centrality* models determined whether language predicts social dynamics above and beyond the random effects. Intraclass Correlation Coefficient (ICC), (Raudenbush & Bryk, 2002), Second-order Akaike Information Criterion (AICc) and a likelihood ratio test (Hastie, Tibshirani, & Friedman, 2009) were used to decide on the best fitting and most parsimonious model. The ICC is commonly used in the model building process to determine the strength of the non-independence or the necessity of additional random variables. In the present study, we started with a simple random intercept model for student within course. The ICC was used to assess the value added by using a more complex model that allowed slopes to vary as well as intercepts. The ICC and AICc likelihood ratio tests indicated the more complex random intercept and slope significantly improved the degree and eigenvalue models, but not the closeness or betweenness models (Table 2). We also estimated an effect size ( $R^2$ ) for each model as goodness-of-fit measures, calculating the variance explained using the method suggested by Xu (2003).

Linear mixed-effects models were conducted using R v.3.0.1 software for statistical analysis with package lme4 (Bates, Mächler, Bolker, & Walker, 2015). The hypotheses specify the direction of the effect, however two-tailed tests were used for significance testing with an alpha level of .05. Model fit assessment and fixed effects for all models are discussed below and reported in Table 2 and Table 3, respectively.

## 5. Results

### 5.1 Degree centrality

A likelihood ratio test indicated that the *full model* yielded a significantly better fit than the *null* and *fixed effects* model (see Table 2). The linear mixed-effects analysis revealed a significant main effect for *Narrativity*,  $F(1, 3097.20) = 4.51$ ,  $p = .034$ , *Referential Cohesion*,  $F(1, 2867.70) = 30.97$ ,  $p < .001$ , *Syntax Simplicity*,  $F(1, 3089.20) = 4.32$ ,  $p = .038$ , *Week*,  $F(1, 3089.30) = 24.69$ ,  $p < .001$  and *Posts Count*,  $F(1, 1733.80) = 1792.98$ ,  $p < .001$ , whereas *Deep Cohesion*, was marginally significant,  $F(1, 3089.00) = 3.31$ ,  $p = .069$ . Specifically, individuals that acquired higher degree centrality expressed themselves using more conversational style discourse with less overlap between words and ideas (i.e. low referential cohesion), more complex syntactic structures, but more deep level cohesive integration (i.e. positive relationship with deep cohesion) (Table 3). Learners with higher activity levels (i.e., those who simply posted more) had higher degree centrality scores. Moreover, as the course progressed, learners tended to connect with their peers less often. We also observed a significant effect of media used,  $F(2, 2833.10) = 84.00$ ,  $p < .001$ . The results indicated that course participants accumulated higher

degree centrality scores within Facebook and Twitter social networks compared to the networks extracted from blogs (Table 3). The effect was probed further by exploring pairwise comparisons of least square means. There were significant differences in the accumulation of degree centrality between blogs and Facebook,  $t(3031.20) = 10.42, p < .001, 95\% \text{ CI } [0.40, 0.59]$ , and blogs and Twitter,  $t(2765.50) = 11.23, p < .001, 95\% \text{ CI } [0.34, 0.48]$ . There was no significant difference between Facebook and Twitter,  $t(2723.70) = -1.85, p = .060, 95\% \text{ CI } [-0.18, 0.005]$ .

### 5.2 Eigenvalue centrality

The likelihood ratio test between the null, fixed effects, and full model revealed a significantly better fit of the model that accounted for variation of students within different courses (Table 2). The model (see Table 3) showed a significant negative effect of Referential Cohesion,  $F(1, 2736.60) = 15.25, p < .001$  and Week,  $F(1, 3081.30) = 6.88, p = .009$ , whereas the effect of Post Count,  $F(1, 2156.30) = 429.13, p < .001$  was significant and positive. Similar to degree centrality, learners who exhibited lower scores of referential cohesion and created higher numbers of posts had higher eigenvector centrality values. Likewise, as the course progressed, eigenvalue centrality tends to decrease. Finally, results also revealed a significant difference between media used ( $F(2, 2523.70) = 85.35, p < .001$ ). Further analysis exploring pairwise comparisons of least square means showed significant differences between each pair of media: blogs vs. Facebook –  $t(2735.50) = 5.27, p < .001, 95\% \text{ CI } [0.18, 0.40]$ , blogs vs. Twitter –  $t(2737.70) = -9.06, p < .001, 95\% \text{ CI } [-0.48, -0.31]$ , and Facebook vs. Twitter –  $t(2170.90) = -12.85, p < .001, 95\% \text{ CI } [-0.80, -0.58]$ .

### 5.3 Betweenness and closeness centrality

The same models were conducted to investigate how linguistic features of computer-mediated communicative utterances predict **betweenness** and **closeness centrality**. Although in both cases a model with a random slope resulted with better overall goodness-of-fit measures (AICc,  $R^2$ , and ICC), the solution for random effects revealed a perfect negative correlation between random effects specified. This outcome indicates that the model overfit the data (Baayen, 2008). Therefore, models with random slope were discarded, and simpler models were used for analysis. Since the *closeness model* did not reveal any significant effect of linguistic properties measured (Table 3), it is not further reported in the paper.



TABLE 2  
INFERENCE STATISTICS FOR THE MODEL FIT ASSESSMENT

Degree						
	$\chi^2$	Df	R <sup>2</sup>	AICc	student	ICC course
Null model			.42	8200.07	.20	
Fixed model	1534.51***	12	.58	6750.03	.11	
Full model	125.34***	14	.62	6629.10	.13	.22
Eigenvalue						
	$\chi^2$	df	R <sup>2</sup>	AICc	student	ICC course
Null model			.36	8379.50	.17	
Fixed model	667.10***	12	.39	7793.68	.08	
Full model	53.41***	14	.43	7744.36	.05	.19
Betweenness						
	$\chi^2$	df	R <sup>2</sup>	AICc	student	ICC course
Null model			.30	8492.89	.12	
Fixed model	368.66***	12	.33	8204.03	.10	
Closeness						
	$\chi^2$	df	R <sup>2</sup>	AICc	student	ICC course
Null model			.27	8663.12	.12	
Fixed model	162.39***	12	.26	8579.34	.10	

Note:  $\chi^2$  values show the differences between the model in the current row and the model in the previous row.  
Significance codes: \*\*\*  $p < .001$

For the betweenness model, the likelihood ratio test between the *null model* and *full model* indicated a better fit of the model that included fixed and random effects (Table 2). The fitted model revealed a significant negative effect of *Referential Cohesion*,  $F(1, 3083.80) = 5.37, p = .020$ , *Syntax Simplicity*,  $F(1, 3100.60) = 5.31, p = .021$ , and temporal factor (*Week*),  $F(1, 3097.10) = 37.19, p < .001$ , as well as a significant positive effect of the *Posts Count*,  $F(1, 2482.00) = 311.47, p < .001$ . Course participants who tended to use *simple linguistic constructs* with higher *referential cohesion* had lower betweenness centrality, while the increase in the *count of posts* was positively associated with the higher betweenness centrality (Table 3). It is important to note that *week* is also negatively associated with betweenness centrality. This might be due to the fact that students tended to engage less often with their peers towards the end of the course. The *media* used also yielded a significant effect on the values of betweenness centrality ( $F(2, 2782.20) = 35.75, p < .001$ ) (Table 3). Further analysis using a pairwise comparison of least square means revealed significant differences between Twitter and blogs ( $t(2847.40) = 7.69, p < .001$ ).

.001, 95% CI [0.27, 0.45]) and between Twitter and Facebook ( $t(2652.70) = 6.09, p < .001$ , 95% CI [0.25, 0.48]).

TABLE 3  
ANALYSIS OF THE FIXED EFFECTS FOR THE MODELS OF THE FOUR MEASURES OF SOCIAL CENTRALITY

Parameters	Degree centrality			Eigenvalue centrality		
	$\beta$	SE	95% CI (2.5% - 97.5%)	$\beta$	SE	95% CI (2.5% - 97.5%)
Narrativity	<b>0.036*</b>	<b>0.011</b>	<b>0.001 - 0.044</b>	0.027	0.013	-0.008 - 0.043
Deep Cohesion	<b>0.032</b>	<b>0.008</b>	<b>0.001 - 0.031</b>	0.013	0.010	-0.014 - 0.025
Referential Cohesion	<b>-0.077***</b>	<b>0.005</b>	<b>-0.038 - 0.018</b>	<b>-0.066***</b>	<b>0.006</b>	<b>-0.036 - -0.012</b>
Syntax Simplicity	<b>-0.031*</b>	<b>0.012</b>	<b>-0.048 - -0.009</b>	-0.009	0.014	-0.035 - 0.022
Word Concreteness	-0.006	0.004	-0.011 - 0.008	-0.012	0.005	-0.015 - 0.008
Facebook	<b>0.163***</b>	<b>0.048</b>	<b>0.403 - 0.594</b>	<b>0.096***</b>	<b>0.056</b>	<b>0.182 - 0.405</b>
Twitter	<b>0.197***</b>	<b>0.036</b>	<b>0.337 - 0.484</b>	<b>-0.190***</b>	<b>0.044</b>	<b>-0.484 - -0.309</b>
Post count	<b>0.604***</b>	<b>0.014</b>	<b>0.575 - 0.632</b>	<b>0.367***</b>	<b>0.017</b>	<b>0.332 - 0.403</b>
Week	<b>-0.063***</b>	<b>0.004</b>	<b>-0.026 - -0.011</b>	<b>-0.040**</b>	<b>0.004</b>	<b>0.003 - 0.021</b>
Parameters	Closeness centrality			Betweenness centrality		
	$\beta$	SE	95% CI (2.5% - 97.5%)	$\beta$	SE	95% CI (2.5% - 97.5%)
Narrativity	-0.001	0.015	-0.030 - 0.029	0.015	0.014	-0.018 - 0.038
Deep Cohesion	0.012	0.011	-0.017 - 0.027	0.025	0.100	-0.009 - 0.032
Referential Cohesion	0.009	0.007	-0.010 - 0.017	<b>-0.041*</b>	<b>0.006</b>	<b>-0.027 - -0.002</b>
Syntax Simplicity	-0.003	0.026	-0.035 - 0.030	<b>-0.044*</b>	<b>0.015</b>	<b>-0.066 - -0.005</b>
Word Concreteness	-0.022	0.007	-0.020 - 0.006	-0.022	0.006	-0.020 - 0.005
Facebook	<b>0.242***</b>	<b>0.065</b>	<b>0.613 - 0.873</b>	-0.003	0.061	-0.123 - 0.121
Twitter	0.001	0.050	-0.101 - 0.099	<b>0.174***</b>	<b>0.047</b>	<b>0.268 - 0.457</b>
Post count	-0.023	0.019	-0.063 - 0.016	<b>0.323***</b>	<b>0.018</b>	<b>0.287 - 0.360</b>
Week	-0.016	0.005	-0.015 - 0.005	<b>-0.100***</b>	<b>0.005</b>	<b>-0.039 - -0.019</b>

Note: All variables are on a normal scale.

#### 5.4 Time and Linguistic features

When we conducted an analysis of variance/co-variance matrix of fixed effects within the four models, we further observed the correlations among fixed effects. All models yielded low or zero correlations between linguistic features, such as Narrativity, Deep Cohesion, Referential Cohesion, Syntax Simplicity, Word Concreteness, and week of the course when they were measured. More precisely, correlation coefficients for the all the models varied from 0.003 to 0.130 (absolute values). The low correlations among the five Coh-Metrix components is compatible with the principal components analysis conducted on the normative TASA corpus which treated each principal component

as orthogonal to the other components (Graesser et al., 2011). We are aware that there are other approaches for assessing the relationships among predictor variables in the analysis, but it was compatible with the claims on the orthogonality of the components and it also shows that linguistic properties did not change over time. On the other hand, it is interesting to note that the highest correlation was observed between the temporal factor and Referential Cohesion,  $-r = -.13$ , for all of the models. Therefore, a more sensitive statistical approach is needed to further assess the temporal changes in linguistic properties.

## **6. Discussion**

### *6.1 Interpretation of results with respect to research questions*

The goal of the current research was to explore the influence of a broad suite of contextual factors in the development of social capital in a cMOOC. First, we adopted a computational linguistics methodology to identify the linguistic profiles associated with social capital. Further, we examined the temporal dynamics of social capital and whether social capital is influenced by any variations in communication media (i.e., Facebook, Twitter, and Blogs) as well as the amount of participant activity.

We observed that both the amount of activity (number of posts) and deep level linguistic characteristics play a role in learner interactions. This finding suggests there is a need for an analysis of the surface level characteristics and a more systematic and deeper analysis of the discourse in order to obtain a comprehensive understanding of the linguistic properties and learners' activities that are associated with the high volume of social connections. Clearly, a learners' level of activity is an important factor. As one might expect, more active learners are likely to grow their influence over the flow of information in a network, and eventually interact with other well-connected participants. This is reflected in the positive relationship between the number of posts and degree centrality, eigenvalue, and betweenness centrality.

A deep linguistic analysis of the interactions also showed that language and discourse features of written messages in cMOOC environments also play an important role in the development of learners' social capital (RQ1). The results indicate that learners with more connections had a linguistic profile that is more narrative with lower referential cohesion and more complex syntax. However, deep cohesion and word concreteness were not consistently significant. Interestingly, discourse with higher narrativity, lower referential cohesion, and more complex syntax is characteristic of oral language and stories rather the academic language of expository text (Graesser et al., 2011; Graesser et al., 2014). Stated differently, the language and discourse used by learners' with more social capital has a more conversational style, which is suitable when speech participants have high common ground (Clark, 1996) and the material is easier to process.

Within the realm of social interaction, the “common ground” perspective is a widely accepted theoretical framework of communication (Knapp & Daly, 2002). Common ground refers to the knowledge and beliefs communicators assume each other shares. In the conversational context, this shared knowledge includes information that captures group membership, co-present experience, and previous shared interactions (Brennan & Clark, 1996; Clark & Brennan, 1991; Knapp & Daly, 2002). For example, individuals in an interaction are able to infer that they share several types of knowledge on the bases of being in a particular MOOC together, observing the same course content, or maintaining a record of what has been previously discussed. According to Clark and Brennan’s framework, common ground plays a central role in determining many aspects of the interaction between individuals, including the communication style (Clark, 1992, 1996; Clark & Clark, 1977; Clark & Wilkes-Gibbs, 1986; Horton & Gerrig, 2005; Schober & Brennan, 2003).

The principal of least effort is one element of Brennan and Clark’s communication framework that seems to have a particular relevance to learners’ discourse in cMOOCs. The principal of least effort posits that achieving and maintaining common ground is an effortful activity for discourse participants, who have a propensity to minimize this effort. Specifically, the least effort principal maintains that individuals use the least amount of cognitive or linguistic effort needed to successfully communicate their message (Brennan & Clark, 1996; Clark & Krych, 2004; Clark & Wilkes-Gibbs, 1986). In these studies, effort is not an all-or-nothing process, but operates in different degrees. How much effort is needed to accomplish and maintain common ground in a given situation is defined by the grounding criterion (Brennan & Clark, 1996; Clark & Brennan, 1991), i.e., the degree of grounding shared by referents that is sufficient for the immediate purposes. For example, suppose two previously unacquainted individuals discuss their political views. The interaction likely demands more effort to be properly grounded, i.e., reconciled with the existing common ground. In contrast, it would be much easier and require fewer resources to convey the same information in a conversation between a 30-year married couple who have accumulated a considerable common ground.

There are interesting interpretations for the current study from the perspective of Clark and Brennan’s Common Ground framework. In the context of this theoretical framework, the interaction between cMOOC participants is a form of collective action requiring participants to coordinate on content and on process (Brennan & Clark, 1996). Coordination on content requires that participants have or develop a shared understanding of what is the object of discussion. Learners that are more centrally located compared to less centrally located students, share more common ground with a larger proportion of other learners. Therefore, a centrally located social position reduces the grounding cost, i.e. the effort needed to build mutual understanding during communication. This would support our results showing learners with more social capital have a more conversational style, with less referential

cohesion, but still maintain a deeper cohesive structure to their communication. At the other end of the spectrum, learners' with less social capital may need to compensate for the lack of common ground between their self and peers by using more cohesive, expository style discourse, which requires more effort.

Below, we provide an illustrative example, from the current dataset, of this relationship between the linguistic features of language and social centrality indicated by four SNA measures. One can compare the text produced two learners, L1 and L2, both participating in course discussions on Facebook.

#### **L1**

1. I was thinking about “originality” and Connectivism a bit (<http://bit.ly>) and found this rather challenging. I'd like to hear other people's views on what “originality” means in a connectivist world. What “uniqueness” does Connectivism allow?
2. Academics are like all other social groups, they tend to cluster around opinions (and counter-opinions). Trouble is to find the middle-ground where opinion cultures meet. This is where productive debate can happen. Compared to the “strong” opinionated camps (for or against) this middle-ground often appears as a rather small zone, with participants always walking the thin line.

#### **L2**

1. Great resource center... thank you, @L3
2. “A candle loses nothing by lighting another candle ...” ~ Mohammed Nabouss, Libyan journalist who was recently killed in Benghazi
3. Thank you for the post ... I had misfiled my url listing :-)

Both learners had the same level of activity, i.e. both made 4 posts. It is apparent that L1 uses a more oral narrative style and a lower referential cohesion, but there were longer sentences that afford more complex syntax. L1 was “better positioned” within the network of learners, indicated by higher degree ( $L1 = 8$ ,  $L2 = 3$ ), eigenvalue ( $L1 = 0.75$ ,  $L2 = 0.27$ ), closeness ( $L1 = 0.01$ ,  $L2 = 0.008$ ), and betweenness centrality ( $L1 = 47.25$ ,  $L2 = 14.67$ ). In contrast, L2 had a more expository style with shorter sentences that pack in more factual content that is referentially connected.

The case of L1 and L2 also illustrates the mobilization of social capital for achieving a specific return (i.e., learning outcome). We observed how learners L1 and L2 were developing social capital over nine weeks of the course. As mentioned, L1 was “better positioned” within the network of learners, with the higher values of degree, eigenvalue, betweenness, and closeness centrality. According to our assumptions, L1 had developed higher social capital throughout the course. The activation of their social capital was nicely shown in week 10, in which learner L1 received 13 replies and 2 “likes” on a post to the Facebook group. In contrast, L2 received no replies and only 1 “like”. This happened, despite the

fact that both posts have been seen by almost 100 peer learners, indicating a high number of latent ties, and yet, L1 was able to activate more connections.

We explored how differences in Twitter, Blogs and Facebook might mediate the development of network positions (RQ2). Although the analyses did not reveal a significant difference between Twitter and Facebook affordances, blogs did appear to cater to the development of connections within a narrower group of people. Such findings can be related to the differences in technological affordances for interactivity, and resonate with the studies on the use of language in different media. For example, Twitter is found to have a potential for *conversationality* (Purohit, Hampton, Shalin, & Amit, 2013), where communicative exchanges show cross-turn coherence online, and can be defined as sustained, topic-focused and person-to-person (Honey & Herring, 2009). This would suggest that the communicative affordances embedded in Twitter enables a higher number of simple, person-to-person conversations among unknown people.

Besides the obvious higher effort required to strike a casual conversation via somebody's blog, in contrast to Twitter, commenting on a blog post or creating a blog post implies more vulnerability and readiness for self-disclosure and indicates a higher degree of commitment and interest than tweets, which are limited to a maximum of 140 characters. However, it would be premature to discard blogs as an appropriate tool for connective courses due to their lower affordances for social capital. Further studies are needed to identify the strength of the interactions mediated through blogs, since blogs linked to each other, tend "to converse" more actively in the entries and comments, if they are on closely-related topics (Herring et al., 2005, p. 9). Such future studies may indicate that blogs are suitable for quality conversations with fewer and more familiar people (i.e., develop strong ties). Simply put, conversations around blogs will occur once social presence is established and the relationships between learners is based on a certain level of mutual trust (Garrison, Cleveland-Innes, & Fung, 2010).

Our findings also show that temporal dimension (RQ3) has a significant impact on the development of the social capital throughout the course. It seems reasonable to expect that social capital increases over time, along with the quantity and the strength of one's connections. However, our study showed that the most significant "contribution" to the development of the social capital is achieved within the first few weeks of the course, as indicated with the negative association between temporal factor and the four-centrality measures analyzed. This might be due to the decreased amount of student interaction as a course progresses. On the other hand, having more connections does not mean that all of them are equally influential. We also observed that learners tend to connect with less influential peers over time. A possible interpretation might be that course participants are not able to identify peers with similar interests from the commencement of the course. Consequently, there is a tendency to initially connect with course facilitators and those highly influential others. As the course progresses and the interactions

evolve participants become more familiar and therefore manage to activate some of their latent ties (Haythornthwaite, 2005), i.e. build connections with those course participants who may or may not have been prominent network participants, but are of relevance to specific individual learners. In order to enable learners to mobilize latent social ties and general knowledge in their networks, it is important to study different technological and pedagogical approaches that can assist in that process early in the course. Publishing user profiles, easily retrievable by others and making learners prior knowledge, skills, and goals is a promising venue for future research.

The measure of a learners' ability to broker information and shape the information flow had two distinct patterns. First, within the first half of the course, ability of course participants to broker information tended to increase. Second, throughout the second half of the course, these indicators decreased. Such patterns may be explained from the perspective of connectivism (Siemens, 2005) and the nature of interactions in online social networks (Kwak, Lee, Park, & Moon, 2010). It seems that in a "chaotic and ambiguous information climate created by networks" (Siemens, 2010) at the very beginning of the course, there is a need for those who are able to share information, and frame the information flow. However, since creating connections through some social media is a low-effort activity, once learners have identified peers with similar interests, they form social groups around common topics, and the importance of central brokers tends to decrease.

#### *6.2 Implications for Research and Practice*

Our research suggests that linguistic analysis methodologies and monitors of learners' activity can be leveraged to determine a learner's position within a network and be used to help foster peer connections. It is no surprise that being an active participant of the learning process yields better outcomes, and in the case of cMOOCs, the skill of interacting with others more actively can predict an increase in learners' overall social capital. However, further investigations need to examine the "characteristics" of individual learners that not only increase the development of social capital but also the mobilization of social capital for a specific return. In this case, the mobilization of social capital is to facilitate the achievement of learning outcomes. For example, a system could provide learners in a MOOC or a regular online course with support on how to coherently construct their ideas and appropriately build on other learners' ideas. Adaptive assistance within learning environments would ultimately lead to better access to social capital – a concept that is well considered to influence student satisfaction, and perceived, and achieved learning outcomes in online settings (Kovanović, Joksimović, Gašević, & Hatala, 2014; Lu, Yang, & Yu, 2013).

It appears that some environments are more effective in facilitating the development of social capital than others. Specifically, Twitter and Facebook provided better opportunities for building connections with peer learners. However, Facebook and blogs were better options when it comes to reaching the

more influential learners within the network. Our analyses confirm that Twitter is the social media platform that enables the best information outreach to all the participants quickly, which is of particular importance early in the course. Although the relationship between language and the temporal dimension requires a more robust analysis than undertaken in the study reported here, it would appear that learners do not change or improve their linguistic and communication skills throughout the course. Perhaps the language and communication skills are traits that are difficult to change. Such findings may indicate that only the students who already possess well-developed connection building skills benefit from activating social capital embedded in the network. If that is the case, the connectivist course design needs to also assist students in navigating networked learning.

Social media in higher education is becoming nearly ubiquitous in the era of digital learning (Bogdanov et al., 2012). Consequently, our investigation of different social media affordances and their potential to support various types of interaction are not limited to the context of MOOCs. The implications of our findings can be transferred to the broader online learning community. Several researchers (e.g., Blaschke, 2014; Corbeil & Corbeil, 2011) have observed that social media platforms are increasingly incorporated into traditional online classroom in order to foster student interaction and support students in developing self-regulated learning skills. However, one of the main conclusions derived from this literature is that cognitive and meta-cognitive development is only partially supported by technology, whereas the synergy of pedagogy and technological affordances should provide an optimal environment for student development. The majority of evidence on the impact of social media on learning has been derived from qualitative insights on studies with small sample sizes (Blaschke, 2014). Thus, our study provides additional insights into the usefulness of various social media in supporting learning in online settings.

Future research needs to investigate different instructional scaffolds and technological affordances that will guide students to develop necessary skills for learning in networked and highly distributed environments of cMOOCs. Those skills, identified as “new media literacies” (Dawson & Siemens, 2014), should enable learners to unlock opportunities afforded by media in such distributed learning contexts. Eventual changes in the linguistic features may also provide insight into an individual’s progress in the development of these literacies. On the other hand, the relationship between language used and learning in networks found in this study indicates that discourse-centric learning analytics, using measures identified within the study presented, could have an important role in creating personalized feedback. Such feedback (timely, personalized and informative) would help course participants develop new media literacies and skills associated with them such as communication and information seeking.



### 6.3 Limitations

The study analyzed interactions between course participants within the three most commonly used social media platforms (i.e., blogs, Facebook, and Twitter). However, some limitations need to be acknowledged. For the automated data collection process, we relied on the gRSShopper as the source for collecting links to blog posts and copies of tweets. Unfortunately, most of the tweets were no longer available through the Twitter API at the time of our data collection (April-August 2014), so we were not able to analyze interactions that would include replies, retweets, and favorites features of the Twitter platform. However, the content (including mentions and hashtags) was preserved. Finally, the study analyzed the data from courses in a specific subject domain. Given that communication in different subject domains is sometimes associated with different communication patterns, it is important to analyze social interactions within courses from a different subject domain.

## 7. Conclusions

This study investigated the context on how learners leverage access to potential social capital in two connectivist MOOCs. The analysis was conducted through linear mixed effects modeling of the relationships between learners' network positions, linguistic and discourse features of the content they created and shared; social media through which the exchanges occurred; the overall amount of learner activity; and the time in course when interactions took place. Our findings indicate that both learner-contingent factors, such as linguistic and discourse features and amount of activity, as well as pedagogy-contingent factors, such as media in use or time in the course, impact an individual's development of social capital. The implications of the study are that facilitators of distributed courses should consider a broad array of responsibilities that include and extend simple network-formation beyond shaping and leveraging the information flows throughout the learning network. In this context, cMOOC facilitators need to assist learners in choosing specific media for facilitating interactions as a best-fit for an individual learner, as well as introducing instructional elements that enhance group and individual communication skills. The study also opens up further investigation of the relationship between social ties and language in use. The findings suggest that both shallow and deep level of analyses of text need to be considered as influencing factors on the development of social ties and network structures.

Beyond the micro-context of learning in a cMOOC, the study emphasizes the learning outcomes and positional goods acquired through scaled interactions by a student of a non-accredited distributed course (Marginson & others, 2004).

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#### 4.4 Publication: Translating Network Position into Performance

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# Translating network position into performance: Importance of Centrality in Different Network Configurations

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## ABSTRACT

As the field of learning analytics continues to mature, there is a corresponding evolution and sophistication of the associated analytical methods and techniques. In this regard social network analysis (SNA) has emerged as one of the cornerstones of learning analytics methodologies. However, despite the noted importance of social networks for facilitating the learning process, it remains unclear how and to what extent such network measures are associated with specific learning outcomes. Motivated by Simmel's theory of social interactions and building on the argument that social centrality does not always imply benefits, this study aimed to further contribute to the understanding of the association between students' social centrality and their academic performance. The study reveals that learning analytics research drawing on SNA should incorporate both – descriptive and statistical methods to provide a more comprehensive and holistic understanding of a students' network position. In so doing researchers can undertake more nuanced and contextually salient inferences about learning in network settings. Specifically, we show how differences in the factors framing students' interactions within two instances of a MOOC affect the association between the three social network centrality measures (i.e., degree, closeness, and betweenness) and the final course outcome.

## Categories and Subject Descriptors

Education; K.3.1 [Computer Uses in Education] Distance learning

## General Terms

Social Processes, Learning

## Keywords

Social network analysis, ERGM, MOOC, Academic achievement

## 1. INTRODUCTION

Social network analysis (SNA) has been one of the most commonly applied methods in learning analytics research [1, 2]. Network approaches can extend analyses beyond the individual level to focus on group dynamics. As such, SNA can provide insight into the quantity and types of interactions or relationships that occur between participants, groups and communities in conventional as well as online settings [1, 3, 4]. Recently, with the development of social networking sites that allow for a relatively straightforward extraction of social networks, the application of SNA in education has significantly increased [1, 5, 6]. However, despite the volume of SNA applied within education research, few studies have fully realized the potential of network analyses to provide new insights into our understanding of learning [3].

Although SNA provides a rich set of tools and methods that help improve the understanding of learning in social networks [3, 7], the majority of the studies utilizing SNA in education are primarily based on examining structural regularities underlying student interactions [4, 8]. Researchers mainly rely on network structural properties (e.g., centrality and density) [9, 10] or generative processes (e.g., triad closure), usually observed in isolation [8], to describe emerging patterns of students' engagement. For example, by examining measures of centrality, embeddedness or triadic closure in social networks, researchers can reveal who is interacting with whom and what is the strength of interactions, the actors occupying more central or peripheral positions in the network, and how such network engagement patterns can affect learning [3, 4, 10, 11]. Although with limited generalizability, such analyses are of great importance in uncovering weak and strong ties that bridge communities/groups of students, revealing the most influential actors or individuals that may have a more advantageous position [12, 13].

The major characteristic of the descriptive models used in the traditional application of SNA in (online) education has focused on *describing* relationships between observed variables, rather than explaining *why* such structure exists [8]. Although models for descriptive analysis help explain the association between network variables and identify potentially relevant processes in

the network structure, they do not allow for the generalization of findings across the networks. The lack of inferential power that characterizes these mathematical, descriptive models (e.g., measuring centrality or density) is indirectly depicted through the interpretation of the association between learning outcome and measures of students' social centrality. Despite the prevailing, and largely unchallenged, understanding that occupying a higher social centrality leads to a higher academic performance [3, 9, 10], research findings are inconclusive about which centrality measure (or combination of measures) is the most significant predictor of academic achievement. Additionally, several recent studies have revealed somewhat contradictory results, indicating that the predictive power of social centrality measures highly depends on the context that frames students' interactions [11, 14].

A potential rationale for explaining the inconsistencies in the educational research may lie in the lack of accountability for the network context that frames social interactions [15, 16]. Research and practice in learning analytics commonly relies on general models (i.e., context independent) in order to inform learning and teaching processes, predict learning outcomes or provide appropriate scaffolds [15]. However, without considering specific learning settings, those models could lead to incomplete conclusions. Likewise, applying SNA without accounting for the processes that guide network formation and consideration of the quantity and quality of interactions could also result in a model that does not reliably capture the underlying social processes [8]. Thus, in order to provide for more valid inferences and identify the determinants that explain regularities of network formation, a sound theoretical approach driving the choice of the analytics methods is required. In so doing, the theory driven approach can help explain the underlying network structure and provide the context for the interpretation of revealed social processes.

### 1.1 SNA and MOOC research

The emergence of Massive Open Online Courses (MOOCs) has provided new opportunities for the application of SNA among researchers and practitioners interested in studying networked learning [17, 18]. Given the high numbers of students enrolling into MOOCs [19] and the immense amount of data related to students' participation and interaction collected by MOOC platforms, it has become even more challenging to understand patterns that drive learning in such networked settings. Therefore, studies investigating MOOCs have relied on SNA methods in order to visualize and examine regularities in interactions emerging from social learning activities that students and teachers engage with [20, 21], as well as to investigate the association between centrality in social networks and student performance [11, 14], to name a few. However, this research while valuable, still fails to adequately account for both context and the structural properties of the established networks.

To address this deficit the present study incorporates both theory related to the importance of "super-strong" ties [16, 22] in network development as well as the statistical methods for generalizing network inference, i.e., Exponential Random Graph Models (ERGMs) [23]. The study analyses two separate instances of the same MOOC offered in different languages during the same period of time. In so doing, the study aims to provide further evidence for the importance of accounting for the contextually salient determinants that define network formation when studying social networks. In the following, we compared two social networks, emerging from student discussions, with respect to the

statistical properties that define underlying network structures [23]. We utilized statistical network analysis (i.e., ERGMs specifically), rather than mathematical (descriptive) methods, as it is a more comprehensive approach to explaining uncertainty inherent in the observed data and determining which of the network processes present significant factors that frame the network evolution [4, 8, 23]. Finally, following the differences in the regularities framing the social relations within the two networks analyzed, we examined the association between social centrality measures (i.e., degree, closeness, and betweenness) and the academic performance (i.e., obtained certificate – *none*, *normal*, *distinct*), within the different contexts.

## 2. BACKGROUND

### 2.1 Social Network Analysis in Educational Research

The initial application of SNA dates back to the 1930s involving a Harvard study that analyzed interpersonal relations and the formation of cliques [24]. The concept of social centrality was first introduced in the 1940s, with a significant uptake noted in the 1950s and the 1960s [9, 24]. Nevertheless, from these early studies it appeared that while the researchers at the time agreed that *centrality is an important structural property of social networks*, there was a lack of consensus regarding what centrality means and how it should be measured [9]. In his seminal work, Freeman (1979) revisited the concept of centrality and identified three network structural properties that should be considered as a measure of centrality – degree, closeness, and betweenness. In formal online courses, SNA studies have aimed at revealing whether and how those structural properties, as defined by Freeman (1979) and others, are associated with learning. However, different studies have often produced contradicting results. For example, Russo and Koesten [25] showed that network *prestige* (in-degree) and *centrality* (out-degree) significantly predict cognitive learning outcomes. Cho and colleagues [26] also concluded that network centrality measures were significantly and positively associated with a students' final grade. However, results from Cho and colleagues [26] also revealed that only closeness centrality was a significant predictor of the course grade. The association between grades and the other two centrality measures – i.e., degree and betweenness centrality – was not statistically significant. Gašević and colleagues [27] also observed a significant association between grade point average (GPA) and two measures of network centrality (eccentricity and closeness centrality) in a fully online master of science in information systems program. However, similar to the Cho et al's [26] study, Gašević and colleagues [27] also failed to find a significant association between GPA and degree and betweenness centrality. Thus, without detailed contextual information it becomes challenging to conclude which of the centrality measures are considered important predictors of a student's overall academic achievement. More simply put, the absence of context limits our understanding of how network position influences student learning.

Research in MOOCs further argues for the necessity to account for various contextual factors when interpreting SNA in networked learning settings. Specifically, contemporary research shows that the association between student centrality in MOOC discussion forums and academic performance, depends on the context of the course [11, 14]. For example, Jiang and colleagues [14], analyzed the association between degree, betweenness and

closeness centrality and student grades within two MOOCs in Algebra and Financial Planning. While the results indicated a significant and positive association between the final course grade and two centrality measures (degree and betweenness) for the Algebra MOOC, none of the measures were significantly correlated with the student grades for the Financial Planning MOOC. Further, the approach applied in the study by Dowell and colleagues [11] differs from the traditional application of SNA in MOOCs. More precisely, Dowell et al. [11] aimed at predicting two different achievement measures— final course grade and social centrality – using linguistic properties of student generated content. Results showed that the linguistic characteristics positively associated with social centrality were negatively associated with the final course grade, and vice versa. Although Dowell and colleagues [11] did not directly compare social centrality and course grades, their findings indicate that these two measures of learning tend to capture different achievement metrics, suggesting further that “the skills associated with these two learning-related outcomes differ” (p.7, *ibid.*).

This review of the existing literature, suggests that future research should provide additional insight into the contextual factors that may impact on the association between students’ position in the network and their learning outcomes. Instead of focusing solely on the network structural properties to describe patterns of students’ engagement within MOOC discussion forums, we aim to utilize statistical network analysis to provide contextual information about the processes that stimulate the underlying network formation. Particularly, we aim to reveal important regularities in interaction structure among the course participants that could provide a valid context for the interpretation of network structural properties. It should be noted that contextual factors are not necessarily related to the course design and instructional conditions. Here, we observe context in terms of the factors that frame individuals’ social behavior. According to Simmel [28] the nature of interaction between the two individuals in a social network is derived from the collective behavior, which accounts for the general social situation that goes beyond the two focal parties.

## 2.2 Simmelian Ties Theory

In addition to the direct measures of the network structural properties, SNA research should also consider the contextual factors that influence the development of the network. The most influential research in SNA argues that those individuals who occupy more central roles (primarily focusing on betweenness centrality) will have higher potential to benefit from such positions and attain their goals [9, 13, 29]. Thus, in his seminal work, Granovetter [13] argued that weak ties are those that enable more straightforward access to information disseminated through a social network. Burt [12] goes even further arguing that the strength of ties is not as relevant as the fact that a given tie bridges otherwise distinct groups or cliques in the social network. As Burt noted “[p]eople whose networks bridge the structural holes between groups have an advantage in detecting and developing rewarding opportunities” [30, p. 354]. Both theories are in line with Freeman’s [9] definition of centrality and assume that the more central persons in a social network occupy a more advantageous position. Nevertheless, Krackhardt [16] posits that centrality does not necessarily imply less constraints and more benefit. If a node is linked in what Krackhardt [16] calls a “Simmelian tie”, such a position could impose additional limitations. In the context of the present study, this could suggest

that while a student centrally positioned in the network has a high potential for control over the information flow, the actual realized gains for their learning may be diminished. Therefore, as Krackhardt [16] posits, traditional SNA analysis (in his case traditional role analysis) should be supported with Simmelian Ties analysis. In the present study, we argue that Simmelian Ties Theory [28] presents a sound theoretical framework in providing valid context for interpreting the importance of social centrality for the academic achievement .

Simmel’s theory of social behavior focuses on studying relationships that occur between people in order to explain their actions [16, 28]. Simmel argued that context is the primary factor influencing what people do and why they behave in a particular manner. Context is determined “by the set of third others who also engage in various relationships with the two focal parties” [31, p. 16]. Thus, as Simmel argued, the establishment of such triadic nodes should be the fundamental unit of analysis in order to understand social behavior [16, 28]. Triads are considered to be qualitatively different from the dyadic relationships that Burt [12] and Granovetter [13], among others, focus on [16, 22]. This difference originates in the nature of the formed relationships. The two nodes forming a dyad are more independent and retain more individuality in their relationship [16, 22]. For instance, should disagreement occur in a dyad, both parties can choose to cease any further interaction. However, a triadic tie requires a higher level of negotiation. If a member of a group disagrees and ceases further interaction the group remains to exist and a connection remains. Thus, Krackhardt [22] described Simmelian ties as “super-strong” (p.24), ties that “qualitatively add durability and power” (p.24, *ibid.*), beyond the strong ties as previously defined by Granovetter [13] and Krackhardt [32].

Simmelian ties theory differs from psychological theories, such as Heider’s [33] balance theory, in explaining structural properties for the existence of symmetric and transitive triples, that are considered main processes in social networks [16]. According to Heider’s [33] theory, people are motivated to establish and maintain relationships that would allow them to keep comfortable communicating with others. The Simmelian theory, on the other hand, assumes that once cliques are formed, they resist changing, becoming strong and stable, thus decreasing propensity to dissolve over time [28]. However, “there is no inherent motivation to form a clique” [31, p. 21], it is rather the social structure, or the context, that causes formation of certain network structures [28].

Building further on one of Krackhardt’s [22] conclusions (i.e., that *traditional* SNA should be supported with Simmelian ties analysis), and given the theorized relationship between the social centrality and the expected benefits, it seems reasonable to analyze whether networks under study exhibit properties of Simmelian ties. In the educational context, such strong ties could indicate the existence of tightly connected groups, focused around common interests.

## 2.3 Exponential random graph models in Online Learning

A majority of studies applying SNA in online and distance education relies on mathematical models to describe relationships between observed variables [34]. Such studies are particularly useful in revealing important network characteristics or what processes should be observed within the social network [8]. For example, using descriptive models we would be able to determine

whether Simmelian ties exist in a given network. However, in order to reveal whether these processes (i.e., propensity to form “super-strong” ties) occur more often than expected if ties were generated randomly, as well as what other micro-level processes (e.g., popularity, propensity for triad closure) determine social dynamics in a given network, we need to rely on statistical models [8]. The quadratic assignment procedure for analyzing dyadic data sets [35], Exponential Random Graph Models (ERGM) and stochastic blockmodels for the cross-sectional social network analysis and community detection [23, 36], as well as longitudinal models for studying evolution of networks and behavior [37] are some of the commonly proposed methods. ERGM specification allows us to model Simmelian statistics (i.e., a process of formation of “super-strong” ties). Hence, this approach is directly applicable for exploring hypothetical network processes that could explain the evolution of the observed cross-sectional network [8, 23].

As a generalization of  $p1$  models and Markov graphs [38], exponential random graph models for social networks, also known as  $p^*$  models, were introduced by Frank and Strauss [39] and Wasserman and Pattison [40]. ERGMs belong to the family of probability models for network analysis that allow for more generalizable inferences over the structural foundations of social behavioral patterns [23, 38]. Observing network ties as random variables, ERGMs allow for modeling overall network structure through a set of local network processes [38]. ERGMs assume that each tie within these local network processes (e.g., mutuality, transitivity or triad closure) is conditionally dependent, indicating further that “empirical network ties do not form at random, but that they *self-organize* into various patterns arising from underlying social processes” [41, p. 3]. Although ERGMs, and similar statistical methods (e.g., longitudinal probabilistic social network analysis – [4]), have been successfully applied in social sciences [42], medical research [43] and studying traditional education [8], their application in the context of online learning and MOOCs is rather sparse.

From the perspective of the analytical methods applied and the educational context analyzed, Kellogg et al.’s [5] study is perhaps the most relevant for our research. In their mixed methods study, Kellogg and colleagues [5] aimed at providing more comprehensive understanding of the dynamic processes that underlie peer support learning in MOOCs tailored towards educators in K-12 settings. The quantitative part of the study included application of SNA tools and techniques – descriptive network measures and ERGMs – in the analysis of the two interaction networks obtained from discussion forums. In order to examine mechanisms of peer support in the two MOOCs, Kellogg and colleagues [5] analyzed various patterns of selective mixing and network statistics: reciprocity, homophily by professional role (e.g., principal), gender, educational background, grade levels, differences in experience (i.e., heterophily), and three proximity mechanisms based on the state or country, geographical region, and group assignment. The results indicate a strong and significant reciprocity effect, suggesting that students are more likely to reply to a peer when there has been prior evidence of reciprocity. Nevertheless, homophily and heterophily effects, as well as proximity mechanisms differed across the networks analyzed.

## 2.4 Research questions

The education literature suggests that researchers predominantly rely on descriptive methods when applying SNA in online

learning settings. There is far less evidence of the research accounting for network specific variables that could provide contextual background for the interpretation of the underlying processes. Given the inconsistencies in findings on the association between social centrality and learning outcome, we aimed at determining whether network social dynamics have an impact on the predictive power of network structural position. We were particularly interested to find out whether a network formed around an online course is characterized by the propensity to form Simmelian ties. We hypothesized that these “super-strong” relationships could influence the potential benefits students derive from occupying more central positions in the network. Thus, we defined the following two research questions:

**RQ1.** *Are there differences in the underlying processes that determine network formation within social networks formed in various online learning settings?*

**RQ2.** *Is the propensity for forming Simmelian ties significantly different than expected if ties were formed randomly?*

Eventual differences in the social dynamics that frame social interactions within the two networks analyzed would provide a valid context for the interpretation of the possible variances in the predictive power of the social centrality measures. Therefore, we defined our third research question as follows:

**RQ3.** *If there are differences in regularities that frame network structure among the course participants, how do these discrepancies affect the association between social centrality and academic performance?*

## 3. METHOD

### 3.1 Data

This study analyzed forum discussions within two instances of a single course that were delivered on the Coursera platform in Spring 2015. The two instances, Code Yourself!<sup>1</sup> (CDY) and ¡A Programar!<sup>2</sup> (APR), were designed to be identical with respect to the content and teaching methods, with the only difference being the delivery language, i.e., English in CDY and Spanish in APR.

The MOOC aimed to introduce young teenagers to computer programming, while covering the basic topics in computational thinking and software engineering. The content of this 5-week course consisted of lecture videos, quizzes and peer-assessed programming projects, which were translated and tailored for English and Spanish-speaking audiences. A common marking scheme was established, whereby students were deemed to have successfully completed the course (and obtained a certificate) when they had a score of at least 50% for the coursework. A distinction was awarded for students receiving a score of 75% or more. CDY and APR were designed to be identical not only in content, but also with respect to their simultaneous delivery with the MOOCs running from March-April 2015. This implies that all aspects of the MOOCs were equivalent including weekly course announcements and matching instructor-initiated prompts in the discussion forums, and adopting a common strategy for minimal instructor intervention in the forums.

Despite the common approach for the two course instances, student engagement and performance was considerably different in CDY and APR. As shown in Table 1, almost 60,000 students

<sup>1</sup> <https://www.coursera.org/learn/codeyourself>

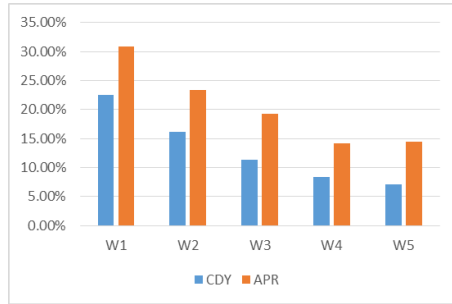
<sup>2</sup> <https://www.coursera.org/learn/a-programar>

enrolled in CDY and more than 25,000 in APR. However, almost the same number of students completed the two courses – 1,597 in CDY and 1,595 in APR. Moreover, regardless the smaller student cohort (in overall), higher number of students engaged with the forum discussions in the APR course, resulting in a more intensive forum activity produced (Table 1).

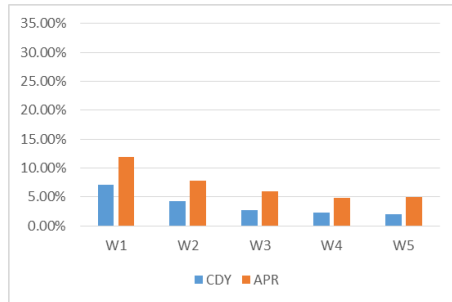
**Table 1. Descriptive statistics for the number of enrolled students, students engaged with the course content and discussion forum, as well as the obtained certificates**

	CDY	APR
Enrolled	59,531	25,255
Engaged	<b>26,568</b>	13,808
Engaged with forum	1,430	<b>1,818</b>
<b>Posted messages</b>		
Threads	776 (1.69; 1.75)	1,081 (3.53; 5.12)
Posts	4,204 (3.13; 7.75)	5,940 (3.53; 5.12)
Comments	1,981 (3.42; 9.06)	2,686 (3.21; 6.75)
Total	<b>5,177</b>	<b>7,409</b>
<b>Obtained certificate</b>		
Normal	586	644
Distinct	1,011	951
Total	<b>1,597</b>	<b>1,595</b>

Note: Thread, Posts and Comments rows display counts in the following format – total (average; SD)



**Figure 1. Proportion of students that watched a lecture each week**



**Figure 2. Proportion of students browsing forums each week**

Large differences were also observed with respect to student engagement with the course materials. The proportion of students that visited the course, watched a lecture, submitted an exercise or browsed the forums each week in CDY was always smaller than the corresponding proportion for APR that week. As depicted in Figure 1 and Figure 2, in some cases this difference reached levels of about 8%. It is also worth mentioning that the weekly engagement steadily dropped in CDY during the 5-week duration.

In contrast for APR there was a steady drop during the first 4 weeks, followed by an increase in engagement for the final week.

## 3.2 Analysis

### 3.2.1 Social Network Analysis

To address the first two research questions, we extracted two directed weighted graphs to represent interactions occurring within discussion forums for the two course instances (CDY and APR). Although several approaches have been proposed for extracting social networks from discussion forums, we relied on the most commonly applied approach that considers each message as being directed to the previous one [11, 44]. For example, if author A2 replied to a message posted by author A1, we would add a directed edge A2->A1. Further, if A3 posted a comment on A2's post, we would include A3->A2 edge as well. Finally, social graph included all the students who posted to the discussion forum.

Social network analysis was conducted through two complementary phases; statistical network analysis and structural (i.e., *traditional*) network analysis. The **statistical network analysis** was performed using ERGMs in order to reveal various networks statistics and examine processes that guided network formation for both of the courses instances. Relying on commonly used network statistics [4, 5, 8] we examined network formation mechanisms at the two levels; dyadic and triadic. At the **dyadic level**, we aimed to investigate the effects of **selective mixing**, **reciprocity**, **popularity**, and **expansiveness**. *Selective mixing* reflects a students' propensity to interact with their peers based on the combination of their individual characteristics [8, 23]. Thus, we considered a homophily effect with respect to the following students' attributes:

- Achievement: none, normal, and distinct;
- Domestic: a student was from either the United Kingdom or Uruguay (as the course was offered by two universities from these two countries) or was from an alternate country,;
- Gender: male, female;
- Access group: student, instructor, or teaching staff.

*Reciprocity*, on the other hand, is a network statistic that models students' tendency to form mutual ties and cluster together [23]. In the case of our study, this property would allow for revealing whether students tend to continue interaction with their peers who replied to their posts. Finally, *popularity* and *expansiveness* tend to model processes that would indicate the existence of students who receive a significant number of replies to their posts or students who tend to reply more often to their peers' posts, respectively.

At the **triadic level**, we examined effects of **triadic closure** and **Simmelian ties** formation. Existing research argues that cyclic and transitive triples are the common characteristics of networks emerging from social media [45]. However, with directed networks, these two statistics are captured within the *triangle* term [8, 23]. Nevertheless, models with *triangle* term are almost always degenerate [23], therefore, *geometrically weighted edgewise shared partner distribution (gwesp)* is used instead. We also modeled Simmelian ties [32] in order to examine whether the network(s) analyzed conform to the Simmelian ties theory. That is, whether the networks exhibit a formation of cliques of students that tend to interact with each other significantly more often than with the rest of their peers. Such a statistic could indicate that those students are primarily being focused on their field of interest and rarely interacting with other students.

The analysis of **network structural properties** relied on most commonly used SNA measures that capture various aspects of graph structural centrality – degree, closeness, and betweenness centrality [9, 10, 34]. Degree centrality is considered the most straightforward centrality measure, focusing on the local structure surrounding the node and indicating the number of connections (ties) a node has in the network [9]. It is commonly interpreted as a measure of *popularity* [34] or the extent to which observed node has a “potential for activity in communication” [9, p. 219]. Given that our focus was on the analysis of weighted networks, we relied on the weighted degree centrality, that accounts for the weight of edges a node has in the network [46]. Closeness centrality measures a distance of a given node to all other nodes in the network [9]. Closeness centrality measures nodes’ potential to connect easily with other nodes. Finally, betweenness centrality is perhaps the most significant for the context of our study, given Krackhardt’s [16] view on the association between the strength of the ties and expected benefits for the nodes that bridge two distinct parts of the network.

We consider three models, for each of the networks, based on the described set of statistics – a demographic attribute model (DM) that includes only processes based on students’ characteristics; triadic closure and Simmelian ties model (TSM), including only *gwesp* and *simmelian* statistics; and a full model that combines the two (FM). Comparing likelihood-based measure of AICc, we further continued selecting the most parsimonious model, which would provide the best fit to our data. The social networks were analyzed using the *ergm 3.1.2* [47], an R package for statistical network analysis, and using *igraph 0.7.1* [7], a comprehensive R software package for complex social network analysis research.

### 3.2.2 Regression Analysis

To examine the association between the dependent variable (i.e., obtained certificate), and the independent variables (i.e., three centrality measures), we adopted multinomial logistic regression (MLR) analysis [48], in order to answer our third research question. MLR is predictive analysis that is used to explain the association between a nominal dependent variable that has more than two levels (*none*, *normal*, and *distinct*), and one or more continuous independent variables [48]. It does not make any assumptions of normality, linearity and homogeneity of variance for the independent variables [48].

Aiming to observe the association between the three centrality measures – degree, closeness, and betweenness centrality – and the course outcome, we build three MLR models. Each model included one dependent (obtained certificate) and one independent variable (degree, closeness, or betweenness centrality). The analyses were performed using the *mlogit 0.2-4* package for R that enables estimation of multinomial logit models [49].

## 4. RESULTS AND DISCUSSION

### 4.1 Network Characteristics

Descriptive statistics (Table 2) indicate rather diverse processes within the two networks analyzed. Given the difference in the number of nodes (Table 2) it is expected that the APR network would have a considerably higher number of edges, and perhaps moderately higher weighted degree. However, higher modularity, average clustering coefficient and higher number of connected components, could indicate a less cohesive group of students within the CDY instance of the course [1]. Moreover, descriptive statistics also indicate a comparable number of reciprocal ties,

whereas the number of “super-strong” ties is considerably higher in case of the English version of the course.

**Table 2. Descriptive statistics for social networks extracted from CDY and APR discussion forums**

Descriptives	CDY	APR
Edges	3,620.00	4,736.00
Avg. W. Degree	4.00	4.69
Density	0.002	0.001
Modularity	0.45	0.33
Conn. comp.	16.00	9.00
Avg. clust. coef.	0.12	0.09
Reciprocity	231.00	176.00
Simmelian	41.00	7.00
Simmelian ties	144.00	32.00
Popularity	758.55	839.00
Expansiveness	1373.42	1612.53

In case of both networks under the study, the full model provided the best fit, indicated by the lowest value for AICc (CDY: DM – 2,830,818.00, STM – 49,863.82, FM – 48,371.14, and APR: DM – 4,577,956.00, STM – 67,786.65, FM – 66,921.94). Estimated coefficients are presented in Table 3, whereas goodness-of-fit statistics indicate that models provide a satisfactory fit for the data. It is also important to note that we aimed at assessing homophily at the level of access groups (i.e., students, teachers, teaching staff) and triad closure (*gwesp*) (Section 3.2.1). However, those two statistics indicated an overall worse fit to our data than the selected (i.e., best fit) model; therefore, both statistics were excluded from the final models analyzed.

**Table 3. Analysis of the estimates for the two ERG models – CDY FM and APR FM**

	CDY		APR	
	Estimate	SE	Estimate	SE
Baseline (Edges)	-5.45***	0.04	-5.81***	0.09
<b>Selective mixing</b>				
Distinct	0.98***	0.03	0.47***	0.12
None	0.15***	0.03	-0.20**	0.08
Normal	0.60***	0.17	0.68**	0.25
Domestic	-0.95***	0.03	-0.09	0.07
Gender	0.02	0.03	-	-
<b>Structural mechanisms</b>				
Reciprocity	3.81***	0.09	4.20***	0.55
Simmelian ties	4.89***	0.61	-	-
Popularity	-3.68***	0.10	-4.75***	0.29
Expansiveness	-	-	-0.25	0.21

Note: \*  $p < .05$ . \*\*  $p < .01$ . \*\*\*  $p < .001$ .

It is revealing that differential homophily for the final course outcome (i.e., obtained certificate) shows that both networks exhibited a higher likelihood of assortative mixing between the students who obtained the certificate. Similar to Kellogg and colleagues study [5], our results suggest that the more successful students tend to interact more often. However, the likelihood of interaction between the most successful students is higher in the CDY course. Whereas, the same effect holds between the students who did not obtain the certificate in case of the English instance of the course (although with less likelihood), the effect is negative in the Spanish version of the course. Students who did not obtain a certificate in the APR instance of the course were less likely to interact with each other.

Homophily for the students’ country of residence, revealed a significant effect for the English instance of the course, whereas



the effect was not significant in the Spanish version. Kellogg and colleagues [5] observed a similar effect - i.e., homophily by state or country) and found a significant positive increase in the likelihood that two students from the same state or country will create a tie. In our study, however, we examined selective mixing between *domestic* students. Given that two courses were particularly designed for two diverse groups of students, we aimed at investigating how that aspect would influence students' tendencies to connect with their peers. Our results revealed that students, who are considered "domestic" in the CDY course instance, were less likely to connect with their *domestic peers*. Observing students' demographic data, we could perhaps expect the same effect within both models, given that similar numbers of students (7% in CDY and 10% in APR) were considered domestic in both networks. However, the observed effect was not statistically significant for the Spanish version of the course.

The effect of reciprocity was significant for the models of both networks, indicating that students tended to continue interacting with peers who replied to their posts. Although the estimates seem rather high, those values are in line with results of Lusher, Koskinen, and Robins [50] and Kellogg et al. [5] studies, who also revealed a very strong effect of direct interaction between students. It appears that a strong effect of reciprocity could be seen as one of the defining characteristics of interaction in online social networks in general [50]. Moreover, Lusher and colleagues [50] further identified such networks as "self-disclosing" (p.249) and "bonding" (p.249), characterized by strong ties relations between the nodes. In such networks, students tend to self-disclose themselves, bonding with their peers, creating comfortable environment for knowledge sharing and learning [50]. However, given rather the low cohesion at the network level for both networks (i.e., low density – Table 2), it seems reasonable to conclude that students commonly interact within smaller groups of peer students [24].

The effect of Simmelian ties was not consistent across both the networks. While it was strong and significant for the CDY network, in the case of the APR course we were not able to fit the model with Simmelian statistics. Thus, although the strong effect for reciprocity could indicate existence of strong ties, it seems that the ties within the English version of the course *evolved* to "super-strong" ties, as defined by [16, 22]. The existence of Simmelian ties beyond the chance level is a significant defining characteristic of the social network emerging from the CDY discussion forum. These ties are structurally embedded within relatively small, highly connected and cohesive groups, commonly referred to as communities [45]. Interactions within those communities are more often and qualitatively different from interactions with other peer students. This finding could be further explained by a "rich-club phenomenon" (p.1), an analogy used by Vaquero and Cebrian [7] to explain "frequent and intense" (p.1, *ibid.*) interactions occurring within relatively small groups of students, where students benefit greatly from these structural arrangements.

The effect of *expansiveness* was not significant in the APR social networks. However, we were not able to fit the model to a satisfactory quality using this network statistics in case of the CDY network. On the other hand, the strong negative effect of *popularity* in the CDY network is also in line with Kellogg's [5] study. Kellogg et al. [5] and Lusher and colleagues [50] argue that such an effect could indicate that all the students have a similar level of popularity and that most likely networks were not "centralized on in-degree" [5, p. 275]. Considering the previous

results (i.e., the strong effect of reciprocity) this result seems quite intuitive. Moreover, given the fact that we observed interactions within a discussion forum, this effect further contributes to the understanding that students in both networks tended to engage into further interaction with their peers, rather than simply posting a message without the intent to contribute the further discussion.

In addressing the **first and second research question**, we were able to conclude that the observed networks differ with respect to the determinants of network formation. The most notable difference is related to the structure of "super-strong" ties, where CDY network exhibit a formation of cliques formed around students who tend to interact within the strong and stable groups of peers, which "resist change" [31, p. 21]. Although the APR network showed the same regularities with respect to reciprocity of interaction and popularity, the effect of Simmelian ties was not present. Finally, the APR network also revealed higher tendency that students would interact more often with higher performing peers.

## 4.2 Social centrality and academic achievement

Analyzing the association between the students' centrality and the final learning outcome further revealed differences between the two networks. Specifically, in the case of the CDY course instance, only weighted degree centrality was significantly associated with the course outcome –  $\chi^2(1) = 9.048$ ,  $p=.011$ . However, multinomial regression analysis showed that an increase in weighted degree significantly increased the likelihood of obtaining certificate with distinction, compared to not completing the course successfully, whereas there was no significant difference between *normal* certificate and failing the course (Table 4). On the other hand, closeness and betweenness centrality were not significantly associated with the course outcomes.

**Table 4. Results of the multinomial regression analysis of the association between social centrality and the final learning outcome (i.e., obtained certificate)**

		Estimate	SE	t
<b>Weighted Degree</b>				
CDY	distinct	<b>0.008*</b>	<b>0.004</b>	<b>2.720</b>
	normal	0.007	0.004	1.618
APR	distinct	<b>0.046***</b>	<b>0.006</b>	<b>7.318</b>
	normal	<b>0.046***</b>	<b>0.006</b>	<b>7.413</b>
<b>Closeness</b>				
CDY	distinct	0.002	0.038	0.046
	normal	0.062	0.066	0.934
APR	distinct	<b>-0.064*</b>	<b>0.030</b>	<b>-2.113</b>
	normal	<b>-0.105**</b>	<b>0.037</b>	<b>-2.816</b>
<b>Betweenness</b>				
CDY	distinct	0.000009	0.000005	1.621
	normal	-0.000003	0.00001	-0.185
APR	distinct	<b>0.0001***</b>	<b>0.00002</b>	<b>5.584</b>
	normal	<b>0.0001***</b>	<b>0.00002</b>	<b>5.562</b>

Note: \*  $p < .05$ . \*\*  $p < .01$ . \*\*\*  $p < .001$ ; Reference levels for each of the analysis was "none" – i.e., student did not obtain a certificate.

The APR social network revealed different patterns. All of the observed centrality measures were significantly related to the likelihood to obtain a certificate – weighted degree,  $\chi^2(1) = 90.217$ ,  $p<.001$ ; closeness,  $\chi^2(1) = 9.679$ ,  $p=.008$ , and betweenness,  $\chi^2(1) = 59.832$ ,  $p<.001$ . Even more so, an increase in each of the centrality measures significantly increased the

likelihood of both – obtaining a certificate with distinction, and a *normal* certificate (Table 4), compared to not completing the course. It should be noted that direction of closeness centrality is opposite to the betweenness and degree centrality – lower values indicate lower distance (i.e., higher closeness) of a given node to all other nodes in the network [10].

There are two important aspects of the findings presented in the previous section. First, we would argue that our results support [16, 22] understanding of the importance of social centrality in providing greater opportunity for well-positioned individuals. Although Krackhardt [16, 22] discusses the potential to bridge between two social groups (i.e., betweenness centrality), we would posit that the importance of the most commonly addressed centrality measures in educational research – degree (to a certain extent), closeness, and betweenness – should be interpreted with respect to the propensity to form Simmelian ties. Following Krackhardt’s [16] argument that “occupying a bridging role can be *more* constraining” (p. 184, *ibid.*), our results show that depending on the given context, a higher social centrality does not necessarily imply a better academic performance. In that sense, we could conclude that those students who are occupying positions between strongly connected groups of students might not be able to benefit significantly from their position. Observed from the perspective of roles, as defined by Krackhardt [16], this finding could further indicate that students within the CDY course instance tended to primarily interact with peers who share the same interests, and perhaps have the same or similar level of knowledge. Nevertheless, further research is needed to address this assumption.

The second important finding of our results relates to the development of an interactive “rich-club” [7]. In their analysis of the relationship between the social structure and performance, Vaquero and Cebrian [7] concluded that students tend to interact within the groups of strongly connected peers. Vaquero and Cebrian [7] labeled those groups as a “rich-club”, where students engage in interaction with their peers at the very beginning of the course, and tend to remain within the same cliques throughout the course. Vaquero and Cebrian [7] further showed that those persistent interactions are maintained between high performing students, whereas low performing students would usually attempt to join those groups later in the course. However, such attempts would usually fail to produce reciprocity in the interaction with high performing students. Thus, those “rich-clubs” or the groups of strongly connected students could be easily connected with Krackhardt’s [16] cliques (i.e., groups of students connected with “super-strong”, Simmelian ties).

From the analysis of the two social networks it would appear that interaction within the CDY discussion forum tended to follow the social structure as noted in Vaquero and Cebrian’s [7] study. This could imply that students within the APR course instance were more socially inclusive, and supportive of their peers who may have joined late in the discussions. On the other hand, it could also mean that the majority of students in the APR course instance were simply engaged in the discussions from the very beginning of the course. Both of these possible interpretations require further research to more comprehensively explain the reasons for the observed differences in social interactions within two different networks of students (i.e., student in CDY and APR course). Nevertheless, it should be noted that we do not assume that those students who attained a more central position in a social graph are necessarily low performing students.

With respect to the **third research question**, our results support the assumption that social centrality in networks that are formed around strongly connected components (i.e., “rich-club” or Simmelian groups, as with the CDY network) is not associated with the final course outcome. Whereas, on the other hand, with *more relaxed* interactions (i.e., the APR network), however still assuming a high level of reciprocity in social ties, social centrality is significantly and positively associated with the course outcome (i.e., obtained certificate). Finally, it should be noted that weighted degree centrality diverges from this pattern to a certain extent (Table 4).

## 5. CONCLUSIONS & IMPLICATIONS

This study investigated the importance of the context that defines students’ social interactions for the association between structural centrality and learning outcome. Primarily, we grounded the theoretical framework in Simmel’s theory of social interactions and Krackhardt’s [16] argument that the “quality of tie itself interacts with the bridging role to produce more constraint on the unsuspecting actor” (p.184), to define network specific properties that would allow us to make more valid inferences. Finally, supplementing descriptive SNA with statistical network analysis and multinomial logistic regression, we were able to conclude that social centrality within the network characterized with “super-strong” ties, does not necessarily imply benefits. On the other hand, structural centrality in the network with reciprocal ties, where all participants have similar level of popularity, yet without a significant effect of “super-strong” ties, is positively associated with the likelihood of obtaining a certificate at the end of the course.

Analyzing roles in an organization, Krackhardt [16] concluded that “traditional role analysis on raw network relations” (p. 208), should be supplemented with the Simmelian ties analysis, arguing further that such an analysis provides “more insight into organizational phenomena” (p.208). Our study extends Krackhardt’s [16] argument in two directions. Primarily, we argue that *any* traditional SNA (not just role analysis), should be supported with the Simmelian ties analysis, as those ties are qualitatively different from weak and strong ties as defined by Granovetter [13], and therefore provide a more comprehensive understanding of social interactions and the dynamics influencing the overall network. Moreover, as a consequence of this theoretical recommendation, it is reasonable to argue that traditional (primarily descriptive) approaches to the analysis of social interactions should be supported by statistical network analysis. Relying solely on mathematical approaches we are able to identify the most significant patterns in the established social interactions. However, in order to understand which of the identified patterns significantly determine network structure and occur beyond the chance, more profound (statistical) models are required [8, 23, 47].

Through the statistical network analysis methods, we were able to provide context to interpret an association between social centrality and academic achievement. Again we refer to the previous work by Krackhardt [16, 22, 31] to explain how Simmelian ties could affect one’s position within an organization. Krackhardt [16] identified those “super-strong” ties as “more enduring, more visible, and more critical than sole-symmetric ties” (p.208), that is, ties that “constrain and influence” (*ibid.*).

One of the imposed connotations of our findings, for both research and practice domains, is the necessity to account for

contextual information when interpreting the potential gains implied by the network structural properties. For example, revealing and visualizing network structure using deeply embedded relations (i.e., Simmelian backbones) [45] could significantly improve the quality of information presented in social learning analytics dashboards, such as the one presented in the work by Schreurs and colleagues [20]. Moreover, providing additional information about the social dynamics should supplement any feedback based on the measures of structural centrality. Likewise, research on predicting association between descriptive network measures and products of learning, in educational settings, should be constructed on valid theoretical assumptions that could support conclusions about inferred social dynamics.

Further research should also integrate temporal dynamics to investigate how certain network processes evolve over time. A promising approach in that direction would be application of Temporal ERGMs [51], or similar models, for studying time-evolving social networks. Moreover, as indicated by Edwards [42] and Kellogg and colleagues [5], as well as in our previous work [11], [52], SNA should be integrated with content analysis to account for the quality of students' contribution. Finally, it should be noted that 39% of CDY students who submitted the survey, stated that English was their first language. On the other hand, 97% of student who participated in APR course and submitted the survey chose Spanish as their first language. However, we were not able to include this information in the model, since majority of students who participated in the course did not submit the survey. This also reflected to the students who participated in the discussion forum. Nevertheless, investigating whether language, as a predominate medium for communication between students in a computer-mediated learning environment [52], influences development of the underlying social processes, presents a promising venue for future research.

Several limitations of our study need to be acknowledged. We analyzed students' interactions within discussion forum in two instances of a same MOOC. Although we relied on a most commonly accepted method for network construction, this approach tends to underestimate the intensity of all the interactions within the given settings. Moreover, analysis of interactions in a more informal settings, such as connectivist MOOC [53], would also contribute to the greater generalizability of our findings. Finally, data from different subject domains (e.g., social science) should be analyzed in order to account for diverse learning settings.

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## 4.5 Summary

The first study in this chapter (Section 4.2) focused on emerging roles that course participants obtain during the interaction within a cMOOC, as well as to what extent such interactions and process of information flow are mediated by technological factors. With respect to the approach used and the analysis focus, this study is framed as what Welser *et al.* (2017) refer to *structural description*, or more recently, description and exploration of structural connections, as introduced by Eynon *et al.* (2016). The study confirmed that, although course facilitators still play an important role (especially in the beginning of a course), the information flow and knowledge building processes also depend on network-directed learners who are willing to engage into and facilitate interaction and knowledge sharing with their peers. Those *knowledgeable others* (Vygotsky, 1978; Kop *et al.*, 2011) represent a “critical set of learners” (Eynon *et al.*, 2016, p.6) who are “responsible for potential information flow in a communication network” (*ibid.*). These emergent social and technical nodes further influenced a development of interest-based groups of learners (or even communities) formed around specific topics in a course.

The study introduced in Section 4.3 further showed that most of the connections among learners, as well as between learners and teachers are established very early in the course. Whereas later throughout the course, learners commonly activate certain latent ties and connect more often with less influential learners. Understanding the dynamics of structural changes in learning networks, however, is not enough to provide comprehensive insights into the learning processes that underly social interactions (Eynon *et al.*, 2016; Goodyear, 2002). Accounting further for discourse exchanged in the process of knowledge building and sharing in learning networks, as well as embracing data from various sources represent a promising way towards obtaining a more comprehensive portrait of factors that frame development of particular social structures observable in a given learning network. Therefore, in this study (Section 4.3), my colleagues and I further explored a broad suite of contextual factors (e.g., social identity or media used) with respect to the development of social outcome in a cMOOC. Thus, in addition to exploring who is interacting with whom and who are those influential learners in the observed learning network, we also showed some of the factors that characterize those learners with higher potential for communication in the observed learning network.

The study (Section 4.3) further showed that not just some of the learners developed more central positions in the observed learning network and developed higher social capital, it also pointed to the importance of the language used as an important factor in the social interaction. The study therefore contends with Eynon *et al.* (2016) and Goodyear and Carvalho (2014a) among others, who argue that not only the structure of interactions is important – it is also the content and process of knowledge construction depicted through language and discourse that is being generated in these interactions. In this study (Section 4.3), I further relied on various linguistic proxies that potentially suggest different levels of cognitive and affective processes (Kovanović *et al.*, 2016; Joksimović *et al.*, 2014), as means to understand these specific aspects of engagement. It was also indicative that those more central

learners had more narrative and conversational style discourse, that further suggests higher common ground shared between participants who are the most influential in the learning network (Clark, 1996).

The final study in this chapter focused on examining an association between two types of learning outcomes – i.e., social and academic outcome – on the examination of the extent to which and under what contextual factors we can rely on student behavioral engagement and social outcome to explain or predict academic outcome (i.e., final course grade). The study introduced in Section 4.3 showed that the tendency to link with peers who have similar social identity has significant implications for understanding the importance of student social positioning in digital educational settings. In that sense, the findings of this study contend with Krachardt's (1998; 1999) argument that higher social centrality does not necessarily implies benefits, showing that this holds in the context of learning at scale. Rather, those benefits are afforded in learning networks that are primarily formed around weak ties as consistent with the social network literature (Granovetter, 1973; Burt, 1995, 2004).

Each study in this chapter illustrates the application of the conceptual analytics-based model introduced in Chapter 2. The primary focus of the studies introduced in Sections 4.2, 4.3, and 4.4 has been on studying learning networks from the perspective of analyzing temporal *dynamics* of emerging social *structures* that characterize learning across diverse settings for learning with MOOCs (Chapter 2). As theorized in the proposed conceptual model (Chapter 2), research introduced in the present chapter also accounts for contextual factors (such as social media used) and individual learners' agency (Chapter 2). Finally, to provide as a part of comprehensive evaluation of the proposed conceptual model, Section 4.3 shows the importance of obtaining insights into the learner generated *discourse* as a factor that affects formation of learning networks emerging from learning with MOOCs.

The next chapter takes somewhat different perspective in studying learning networks. Specifically, two studies presented in Section 5 are primarily rooted in discourse-based analysis showing the importance of understanding learner generated content in learning process (Eynon *et al.*, 2016; Goodyear, 2002, 2004; Jones, 2015). However, both studies also show that understanding learning networks requires comprehensive insight into the structure, discourse, and dynamics of interactions in learning with MOOCs.

## Discourse-Based Perspective for Studying Learning Networks

## 5.1 Preface

As a complementary approach to the methods introduced in [Chapter 4](#), this chapter introduces two studies that focus primarily on examining discourse as means for explaining knowledge building and sharing processes in learning networks. Analyzing content of learner generated discourse in learning networks represents one of the primary challenges in networked learning research ([Goodyear, 2004](#); [Jones, 2015](#); [Jones and Steeples, 2002](#)). Therefore, the two studies introduced in this chapter examine discourse as means for developing “interpretative models” ([Eynon et al., 2016](#), p.8) that could potentially provide more comprehensive insights in learning processes in networked settings. However, discourse is not an isolated process but one that emerges from the interaction among learners in networked settings. This further implies that the student-generated content should be observed as inherently social, whereas the meaning of discourse could be operationalized only through the social adoption ([Stahl, 2004](#)). Therefore, this chapter also highlights the importance of accounting for the structure of social interaction and shows to what extent actions reflected through language and discourse help in explaining emerging social structures.

The first study in this chapter ([Section 5.2](#)) relies on a pragmatic research paradigm ([Tashakkori, 2012](#)) to investigate factors that shape learners’ interests in the context of learning networks emerging from learning in a cMOOC. In that sense, this study extends research introduced in [Section 4.2](#), by providing a complementary perspective in understanding underlying learning processes. The study moves beyond analyzing social interactions and emerging roles and also takes into consideration the most prominent topics discussed in the knowledge sharing and building process. Specifically, utilizing content analysis techniques (i.e., automated concepts extraction), graph theory, and qualitative analysis of learner generated content across the several social media used by learners, the study proposes a scalable analytic approach to the analysis of learners discourse in a learning networks. Thus, from the perspective of the conceptual analytic-based model introduced in [Chapter 2](#), the study primarily focuses on investigating learner generated *discourse* and *dynamics* of the evolution of topics learners engage with, observing therefore two dimensions of learning networks as defined in the student model introduced in [Section 2.2](#). From the evidence and task model perspectives ([Section 2.2](#)), and conceptual model operationalization proposed in [Chapter 3](#), the first study focuses on *cognitive* and *behavioral engagement*, within the *context* of three social media platforms (i.e., Twitter, Facebook, and blogs).

The second study in this chapter, and the final publication included in the thesis, provides perhaps the most comprehensive analysis of the relations between the three factors that comprise the conceptual analytics-based model – i.e., discourse, structure, and dynamics. In a broader context of computer supported collaborative learning, the literature recognizes various approaches to the study of collaborative discourse ([Marbouti and Wise, 2016](#); [Stahl, 2004](#); [Stahl and Rosé, 2011](#); [Jones and Steeples, 2002](#)). One of the main premises of existing approaches in studying discourse in online learning is that processes of knowledge building and sharing are socially situated and influenced by learners’ interactions with teachers and their peers. [Stahl \(2004\)](#), for example, proposes a framework for studying collabo-



rative learning activities that focuses on analyzing meaning expressed in discourse generated through the process of knowledge construction. Every learner generated artefact, [Stahl \(2004\)](#) contends, obtains a meaning from its position in a sequence of interactions. Therefore, the second study in this chapter ([Section 5.3](#)) observes conversation dynamics of learner discussions to provide a link between processes of knowledge building and resulting social interactions emerging from learning networks. In so doing, this study introduces a novel analytics-based approach that combines discourse and (statistical) social network analysis that allows for examining the evolution of knowledge building and emerging social structures.

## **5.2 Publication: Towards understanding emerging discussion topics in learning networks**

The following section includes the verbatim copy of the following publication:

[Joksimović, S.](#), Kovanović, V., Jovanović, J., Zouaq, A., Gašević, D., Hatala, M. (2016). What Do cMOOC Participants Talk About in Social Media?: A Topic Analysis of Discourse in a cMOOC. Proceedings of the Sixth International Conference on Learning Analytics & Knowledge (LAK'16), pp.156–165

# What do cMOOC participants talk about in Social Media?

## A Topic Analysis of Discourse in a cMOOC

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### ABSTRACT

Creating meaning from a wide variety of available information and being able to choose what to learn are highly relevant skills for learning in a connectivist setting. In this work, various approaches have been utilized to gain insights into learning processes occurring within a network of learners and understand the factors that shape learners' interests and the topics to which learners devote a significant attention. This study combines different methods to develop a scalable analytic approach for a comprehensive analysis of learners' discourse in a connectivist massive open online course (cMOOC). By linking techniques for semantic annotation and graph analysis with a qualitative analysis of learner-generated discourse, we examined how social media platforms (blogs, Twitter, and Facebook) and course recommendations influence content creation and topics discussed within a cMOOC. Our findings indicate that learners tend to focus on several prominent topics that emerge very quickly in the course. They maintain that focus, with some exceptions, throughout the course, regardless of readings suggested by the instructor. Moreover, the topics discussed across different social media differ, which can likely be attributed to the affordances of different media. Finally, our results indicate a relatively low level of cohesion in the topics discussed which might be an indicator of a diversity of the conceptual coverage discussed by the course participants.

### Categories and Subject Descriptors

J.1 [Administrative Data Processing] Education; K.3.1 [Computer Uses in Education] Distance learning

### General Terms

Human Factors, Algorithms

### Keywords

Connectivism, Content analysis, SNA, cMOOC

## 1. INTRODUCTION

The initial development of Massive Open Online Courses (MOOCs) dates back to 2005, and coincides with the ideas of connectivism and networked learning [1]. While the first publicly available MOOC was the Connectivism and Connective Knowledge (CCK08) course in 2008, it was in 2011 when MOOCs started gaining significant attention [2]. Although

MOOCs very quickly became an important component of the adult online education, there is presently an extensive debate about their role in higher education [3, 4]. The main concerns are related to the effective scaling-up of traditional courses and the ability of MOOCs and their underlying pedagogy to meet the needs of higher education [3].

Within the last several years, two prominent types of MOOCs evolved. The more centralized type of MOOCs – xMOOCs – are focused on content delivery to large audiences, where the learning process is teacher-centered, i.e., based on transferring knowledge from instructors to learners [5]. xMOOCs are usually delivered using a single platform (learning management system), where learners receive knowledge (most commonly in a video format), and further apply that knowledge in projects defined by the teacher [5]. On the other side of the spectrum, more distributed MOOCs emerged (cMOOCs). In cMOOCs, teachers' role is primarily focused on the early instructional design and facilitation. cMOOCs do not rely on any centralized platform but rather use various social media for sharing information and resources among learners. The main goal of learning in cMOOCs is knowledge building through connection and collaboration with peers [6]. Learners are co-creators of the content and there is no formal evaluation of the learning achievements.

The most commonly indicated issues and challenges related to MOOCs are low course completion rates, high degree of learner attrition, and the lack of a theoretical framework that would allow for better understanding of learning processes in networked learning [7]. In their analysis of the research proposals submitted to the MOOC Research Initiative<sup>1</sup> (MRI), [7] showed a promising upturn in addressing a wide variety of the challenges recognized to date. Majority of submissions proposed well-established frameworks in educational research and social sciences as a foundation for examining and understanding learner motivation, metacognitive skills, and other factors that shape learning and teaching in MOOCs.

However, our literature review indicates that most of the current studies on cMOOCs are based on quantitative methods and rather simple metrics (e.g., the frequency of facilitators' and learners' postings) [8, 9]. Without the capacity to explain practice and

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<sup>1</sup> <http://www.moocresearch.com>

complexity of networked learning, existing approaches and research models do not allow for understanding of learning at scale [10]. To contribute to the current research practices in this area, our study proposes a combined use of automated content analysis and social network analysis (SNA) in order to provide a more effective approach to MOOC research. More precisely, the study reported in this paper suggests an analytic method that integrates quantitative (automated content analysis and SNA) and qualitative analysis of posts created within different social media platforms used in a cMOOC. Relying on tools for automated concepts extraction, as well as SNA tools and techniques, we were able to identify main groups of concepts emerging from learners' posts and to analyze how they evolve throughout the course. Further qualitative analysis enabled a more in-depth interpretation of our findings.

Having that cMOOCs often incorporate various technologies into the learning process, our first objective was to examine how different social media influence the discourse of course participants. The second objective was related to the role of course facilitators in a cMOOC. More precisely, our objective was to analyze how course readings, suggested by course facilitators, frame the topics being discussed among learners. Finally, we were interested in analyzing learners' discourse through a temporal dimension, that is, how topics discussed by students changed over time, when certain topics emerged and whether we can identify topics that sustained throughout the course.

## 2. THEORETICAL BACKGROUND AND RESEARCH QUESTIONS

### 2.1 Connectivism and cMOOCs

The theoretical foundation behind cMOOCs is connectivism [1, 11] and its principles of autonomy, diversity, openness and interactivity [12]. Connectivism is proposed as a novel theory of learning for "the digital age" [13]. It assumes abundance of information and digital networks, and views learning as the development and maintenance of networks of information, resources and contacts [14]. Primary activities in connectivist learning are [12]: i) aggregation, ii) remixing, iii) repurposing, and iv) forwarding of resources and knowledge.

Teaching in connectivist setting differs from common practices in distance and online education. In particular, teaching is focused on instructional design and learner facilitation, while the course content is created by course participants (i.e., learners and facilitators) [5, 6]. Kop et al. [15] therefore argue that the key to cMOOC success is a combination of teaching and social presence that enables an effective facilitation of learners' self-regulation of learning, which in turn leads learners to the accomplishment of worthwhile, personalized and authentic learning outcomes. Instead of being a distant "rock star" academic of xMOOCs [16] [p. 58], a teacher in cMOOC is expected to be a role model [14], and a discussion moderator rather than a tutor [12]. According to Kop et al. [15], instructors are "*aggregating, curating, amplifying, modeling, and persistently being present in coaching or mentoring. The facilitator also needs to be dynamic and change throughout the course*" [p. 89]. For this delegation of content creation from the instructor to the network, Yaeger et al. [9] emphasize the need for a strong core of active participants that would provide the critical mass of activity.

A typical design of a cMOOC assumes collaboration between course participants using various social media (e.g., blogs, Twitter, Facebook, Google+, RSS feeds and mailing lists) [17]. The use of particular tools and their affordances can directly influence and support the community formation [18], which is essential for learning within cMOOC environments. Twitter

hashtags are probably the best example of technological affordances that can affect community formation [19]. However, the abundance and diversity of technology in cMOOCs is also a challenge [20]–[22], and a source of potential disconnect between the sub-communities in the course [14]. For example, a study by Mackness et al. [21] found that variations in the level of expertise and use of different platforms lead to the development of sub-communities which reduced possibilities for autonomy, openness and diversity. While cMOOC literature acknowledges the importance of technology for shaping learning experience, the effects of particular technologies are rarely discussed [3].

The cMOOC literature so far has mainly focused on descriptive methods for research and analysis of learning in a networked environment. Perhaps, the most comprehensive approach was applied in the study of Fournier et al. [23], who relied on counts of contributions/posts (e.g., Moodle discussion blogs, Twitter), survey, virtual ethnography, discourse analysis and educational data mining, in order to describe learning processes in the PLENK cMOOC. However, their discourse analysis relied on manual coding of messages, a highly time consuming process, while the quantitative methods applied (i.e., clustering and correlational analysis) did not provide a more detailed insight into the underlying learning processes. Although studies by Kop [9], and Yeager et al. [20] adopted social network analysis, the application was limited to the illustration of interactions within the course discussions. Finally, Wen et al.'s [24] study on discourse centric learning analyzed the association between learners' discourse and attrition in a MOOC, using the Latent Dirichlet allocation approach. However, they did not consider the principles of connectivism, nor did they consider different social media platforms.

### 2.2 Research questions

While the number of studies about MOOCs is growing [25], there have been very few studies that looked into the effects of particular choices of technology on shaping learning in cMOOCs. The exceptions are studies by Fini [17] and Mak et al. [26]. However, they primarily focused on quantitative analysis of interactions, media affordances and learning approaches, which did not provide insights into the content of learners' discussions. In our study, we wanted to examine learners' discourse in different social media that are typically used in cMOOCs – i.e., Facebook, Blogs and Twitter. The main objective was to obtain an insight into the topics that learners mentioned in their posts, and how these topics differ across different media. Accordingly we defined our first research question as follows:

**RQ1:** *Do topics discussed by learners differ across social media used in a cMOOC?*

In such a dynamic environment, where learners are encouraged to choose what they want to learn and make sense of the high volume of available information through sustained collaboration with other learners in a network, we were interested in examining the role of facilitators in shaping the discussions in the course. While the study by Skrypnik et al. [27] identified the key role of a small number of active facilitators and technological affordances in shaping the information flow and formation of interest-based communities, it is still an open question how much these communities remain within the original course curriculum suggested by the instructors. Given that cMOOCs are typically organized as a series of online events led by respected facilitators in a particular domain [15], it seems reasonable to analyze how much influence those facilitators have on shaping the overall discussion between learners. This is likely related to the level of autonomy of learners, their self-regulation of learning, and their

particular learning goals. Therefore, we defined our second research question:

**RQ2:** *To what extent do the readings suggested by the course facilitators shape the topics discussed by learners in social media in a cMOOC?*

We were also interested in examining whether the discussed topics stabilize over time or perhaps change in accordance with the changes in the course's weekly topics. This led us to our third research question:

**RQ3:** *How do topics discussed by learners change over time in a cMOOC across different social media?*

Finally, we aimed at providing a scalable approach for a comprehensive analysis of learners' discourse in cMOOCs. The study by Skrypnik et al. [27] examined the use of particular Twitter hashtags over time and thus, to some extent examined the content of learner messages and their evolution over time. Still, our study provides a more comprehensive coverage of learners' generated discourse by investigating blog posts, Twitter messages and Facebook discussion messages.

### 3. METHODOLOGY

#### 3.1 Study context

To get a better insight into the emerging topics in a cMOOC and answer our research questions (RQ1-3), we analyzed the content created and exchanged through social media in the scope of the 2011 installment of the Connectivism and Connective Knowledge (CCK11) cMOOC (<http://cck11.mooc.ca/>). The CCK11 course was facilitated through 12 weeks (January 17<sup>th</sup> – April 11<sup>th</sup> 2011), with the aim of exploring the ideas of connectivism and connective knowledge, and examining the applicability of connectivism in theories of teaching and learning. The topics covered throughout the course included: i) What is Connectivism?, ii) Patterns of Connectivity, iii) Connective Knowledge, iv) What Makes Connectivism Unique? v) Groups, Networks and Collectives, vi) Personal Learning Environments and Networks, vii) Complex Adaptive Systems, viii) Power and Authority, ix) Openness and Transparency, x) Net Pedagogy: The Role of the Educator, xi) Research and Analytics, and xii) Changing Views, Changing Systems. The course participants were provided with readings recommended by the course facilitators for each theme covered by the course (one theme per week). The facilitators encouraged learners to "remix" and share their new knowledge through various means including blogs, Twitter and Facebook<sup>2</sup>. The participants were also provided with daily newsletters that aggregated the content they created and exchanged through these blogs, tweets and Facebook posts. Content aggregation was done using gRSShopper. Finally, the course included weekly live sessions that were carried out using Illuminate.

#### 3.2 Data Collection and Analysis

The overall process of data collection and analysis was done in several steps that are outlined below.

*Collection of learners' posts and recommended readings.* We relied on gRSShopper to automatically collect blog posts and tweets, while Facebook posts were obtained using the official Facebook API<sup>3</sup>. All posts were stored in a JSON format for further processing. Table 1 provides descriptive statistics of the posts collected. Besides posts, we also collected readings recommended by the course facilitators for each theme covered by

the course. The recommended readings appeared in the course outline<sup>4</sup> for each week of the course.

*Semantic annotation of learners' posts and recommended readings.* Having collected learners' posts and recommended readings, the next step was to semantically annotate them, i.e., to associate their content with concepts that reflect the semantics of those posts and readings. To this end, we examined and tested several state-of-the-art semantic annotation tools, including TagMe<sup>5</sup>, WikipediaMiner<sup>6</sup>, Alchemy API<sup>7</sup>, and TextRazor<sup>8</sup>. Based on the analysis of the annotations produced by the examined tools on a sample of the collected posts, and also based on the previous examinations of these tools reported in the literature (e.g., [28-30]), we made the following decision: short posts (tweets and Facebook messages) were annotated using TagMe, while Alchemy API was used for the annotation of longer posts (i.e., blog posts) and recommended readings. Both tools annotate content with Wikipedia concepts which made all the annotations consistent (i.e., based on the same concept scheme).

Since today's annotators mostly operate on English texts, we made use of a freely available language translation tool (Microsoft Translation API<sup>9</sup>) to translate non English posts (5% of our dataset) to English. Even though the resulting translations were not ideal, in most cases, we noticed that they preserved the gist of the original content.

Having inspected the annotations of posts and readings, we identified certain invalid concepts originating from the imperfection of today's semantic annotators. To reduce a potential negative impact on further analysis, we manually removed all concepts that were obviously erroneous (e.g., concept 'cable television' was identified as a disambiguation of the term 'networks', or 'environmentalism' was associated with '[learning

**Table 1. Descriptive statistics of the collected data: number of active learners, post counts (total, average, SD), and word count for each media analyzed**

Media	Active participants	Post count	Average post count (SD)	Word count
Blog	193	1473	3.13 (4.80)	428626
Facebook	78	1755	5.03 (5.23)	67883
Twitter	835	2483	1.80 (3.85)	43180
<b>Total</b>	<b>997</b>	<b>5711</b>	<b>-</b>	<b>539689</b>

environments'), as well as concepts that could not be considered valid in the context of our analysis (e.g., Lady Gaga's songs). Once we created a list of erroneous concepts, the removal was done automatically – before including a concept, we would ensure that the concept is not specified within the list.

*Creation of concept co-occurrence graphs.* The extracted concepts served as an input for the creation of undirected weighted graphs for each week of the course and each media analyzed (36 graphs in total). Aiming to identify the most important concepts and their connections, we created graphs based on the co-occurrence of concepts within a single post. For example, if concepts C1 and C2 appeared within the same post, the two concepts were included in a graph as nodes and the edge

<sup>4</sup> <http://cck11.mooc.ca/outline.htm>

<sup>5</sup> <http://tagme.di.unipi.it/>

<sup>6</sup> <http://wikipedia-miner.cms.waikato.ac.nz/>

<sup>7</sup> <http://www.alchemyapi.com/products/alchemy/language/concept-tagging/>

<sup>8</sup> <http://www.textrazor.com/>

<sup>9</sup> <http://msdn.microsoft.com/en-us/library/dd576287.aspx>

C1-C2 was created. Each edge was assigned a weight representing the frequency of co-occurrence of the two concepts.

*Clustering of concepts into topics (concept clusters).* To further analyze relationships between concepts in the constructed graphs, and extract clusters of concepts, we applied a modularity algorithm for community detection [31]. The initial analysis revealed a rather high number of clusters (over 50 on average, in case of Twitter graphs), with very few large groups and a significant number of small clusters (individual concepts or pairs of concepts). Therefore, we decided to extract the largest connected component in each graph, and use these components for cluster detection [36–38]. The size of the largest connected components used in the study varied from 88% to the size of the total graph in case of blogs, from 78% to 94% in case of Facebook, and from 52% to 86% of the total graph size in case of graphs extracted from Twitter.

In order to better understand emerging topics (i.e., clusters of concepts), we performed an in-depth qualitative analysis. We initially examined concepts within each cluster, aiming to reveal potential patterns that would provide description for the cluster analyzed. In cases where such a pattern could not be revealed, we focused on the content of the messages that these concepts were extracted from, to provide a better context for our interpretation.

*Computation of graph metrics.* The constructed graphs were analyzed using graph metrics that are commonly used for analysis of collocation networks [35]:

- *Graph density* – the ratio of existing edges to the total number of possible edges,
- *Weighted cluster density* – for each of the clusters we first calculated its graph density, and then calculated weighted average cluster density, where weights are cluster sizes.
- *Radius* – the minimum eccentricity among all nodes,
- *Diameter* – the maximum distance between two nodes,
- *Network centrality measures*, namely weighted degree (the count of edges a node has in a network, pondered by the weight of each edge) and betweenness centrality (the indicator of node’s centrality in a graph).

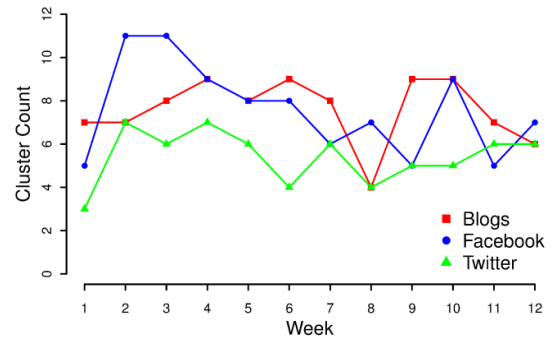
The first three metrics were used to measure the level of coupling/spread of concepts (i.e., coherence) discussed in the analyzed posts, whereas the centrality measures served to measure the importance of individual concepts. Specifically, higher degree centrality should indicate concepts that are associated with many other concepts, while higher betweenness centrality could be seen as an indicator of concepts that could potentially “bridge” two or more topics [36]. Moreover, the selection of these metrics was motivated by the findings of contemporary research on automated assessment of learner generated content and information extraction. For example, Whitelock et al. [33] used keyword-based graphs for automated essay assessment and automated feedback provision. Their study showed that highly connected and dense graphs indicate better structured essays [37]. Building further on the research in computational linguistics, we expected that graphs with higher density would imply a more cohesive and coherent text [38]. Using the measure of degree, density, radius, and diameter, we aimed at examining whether and how the use of different media influences the “structure and cohesiveness” of the content being generated.

*Computing similarity of posts as well as posts and recommended readings.* To answer our research questions, we also needed to examine if there were topics of pertaining interest/relevance to learners, so that they kept discussing them even after the course progressed to other topics. To this end, for each social media analyzed, we computed the cosine similarity [39] between concepts discussed in each pair of consecutive weeks (i.e.,

concepts extracted from posts in the corresponding two weeks). In particular, we relied on a vector representation of the concepts discussed each week, and used the cosine similarity metric to compute similarity between concepts in two consecutive weeks. In a similar manner, we computed similarity between concepts discussed in posts and those discussed in recommended readings. In this case, the readings recommended for week  $k$ ,  $k=1..11$  were compared to posts in each succeeding week ( $k+1$ ,  $k+2, \dots$ ). The idea was to identify learners’ interest in the course themes, based on the assumption that learners would discuss more topics that they find interesting/relevant.

## 4. RESULTS

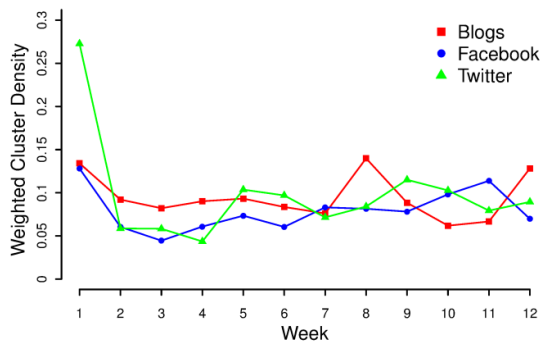
In order to gain an initial insight into the topics discussed in each media channel, in Figure 1 we report the number of identified topics (i.e., concept clusters) identified and the most dominant topics for each media and each course week (Table 2, expressed as the percentage of the graph size, e.g., T1(45%)). We also examined the strength of relationships between concepts within the identified clusters (Figures 2 and 3); how concepts from different media relate to one another (Figure 4); the dynamics of concepts over the length of the course – whether and to what extent they changed from week to week (Figure 5 and Table 2), and how they relate to the recommended readings (Figure 6).



**Figure 1. Topic (i.e., cluster of concepts) count per week per media**

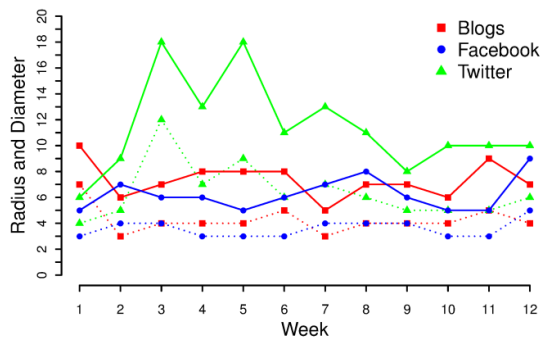
Figure 1 shows the number of detected topics (i.e., concept clusters) per week, for each media analyzed. Within the first half of the course, the highest number of topics was extracted from Facebook posts (except for week 1), while the messages exchanged on Twitter showed the lowest number of topics throughout the course.

Density of concept clusters for all analyzed social media follows quite a similar pattern throughout the course (Figure 2). Aiming to better understand the emerging concept clusters (i.e., topics), we calculated graph density for each individual concept cluster, per media and per week. It is interesting to note that the highest density among the media was observed in the first week of the course, for the concept clusters emerging from tweets. There are also two peaks where density increased notably; for blogs within the week 8, as well as by the end of the course in case of Facebook. These phenomena are analyzed in more details in the Discussion section.



**Figure 2. Average density of concept clusters per week and per media**

Figure 3 further shows how concepts within topics (i.e., concept clusters) were coupled in terms of graph radius and diameter. The results show that concepts extracted from Facebook and blogs posts were more tightly coupled than those extracted from Twitter posts, which seems to indicate more homogeneous and related discussions overall on these two media. As the course progressed, concepts from tweets became more tightly coupled, while for Facebook and blog posts, the coupling of concepts remained approximately at the same level.

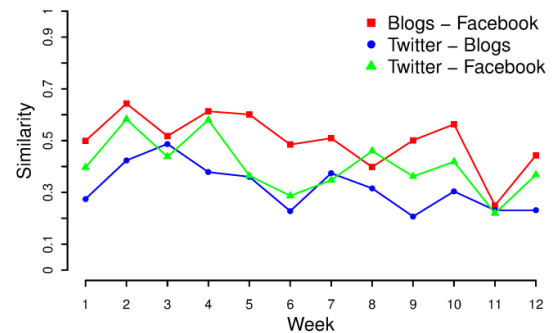


**Figure 3 Radius (dotted lines) and diameter (solid line) of concept clusters measured per week and per media.**

Figure 4 describes similarities between concepts discussed in each media. Comparison of concepts extracted from blogs and Facebook posts yielded the highest similarity over the 12 weeks of the course. On the other hand, concepts extracted from Twitter and blog posts showed the highest discrepancy throughout the course. It is also interesting to note the decline in similarity within the week 11, for each pair of media compared.

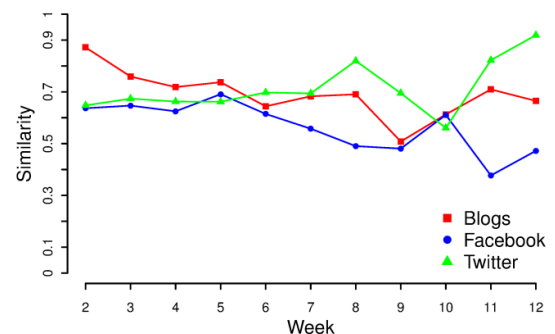
In order to further examine the dynamics of concepts being discussed, we calculated the similarity between concepts extracted from posts in each pair of consecutive weeks (e.g., for week 4, we calculated the semantic similarity of concepts from weeks 4 and 3). As a measure of semantic similarity, we calculated the cosine similarity between vectors of concepts for each pair of consecutive weeks. Figure 5 shows that in all media channels, the concepts discussed by learners remained rather similar from week to week. In case of Twitter posts, similarity between two consecutive weeks tends to increase over time (except for weeks 8

to 10), while in case of blogs and Facebook, we were able to observe a decrease over time.



**Figure 4. Similarity of concepts discussed in different media**

We also analyzed semantic similarity between concepts extracted from posts exchanged on each media and recommended readings for i) the same week, and ii) all the previous weeks. For example, for week 7, we calculated similarity between concepts extracted from blogs, Facebook and Twitter in week 7, and concepts extracted from readings recommended in weeks 1 to 7. This analysis revealed a quite consistent pattern over the three media. Figure 6 shows that concepts extracted for each week, within all three media, were the most similar to the readings assigned for weeks 1-3, and 9. On the other hand, based on the extracted concepts, readings assigned for weeks 4 to 8 had the lowest similarity with posts from any of the course weeks. Moreover, among the three media analyzed, results show that Twitter posts (i.e., concepts extracted from Twitter posts) differed the most from the content presented in the readings for each week of the course, while blogs seemed to be the most similar to the readings.



**Figure 5. Similarity of concepts discussed in two consecutive weeks (per media)**

Table 2 shows the top three topics (i.e., concept clusters) for each media and each week. Topics are ranked based on the number of concepts they consist of. For each topic, the table shows the top three concepts ranked based on their betweenness and degree centrality. Among those highly ranked concepts *connectivism*, *learning*, *e-learning*, *education*, *social media*, and *knowledge*, were most commonly represented within one of the three topics for most of the weeks, within each media analyzed.

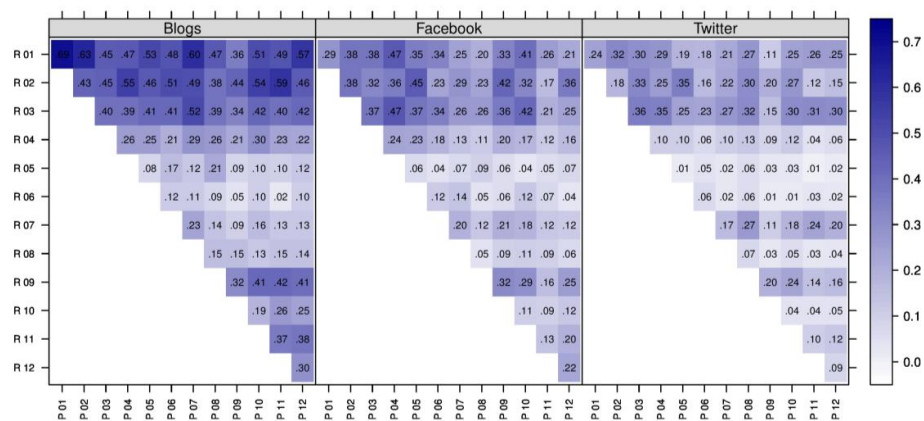


Figure 6. Similarity between weekly readings and posts from each week

An in-depth qualitative analysis of these results allowed us to provide a more detailed interpretation of the topics covered within each week, for each of the three media.

By analyzing topics identified in Twitter messages, we were able to identify the following five groups of topics:

- Within the first group of topics we recognized posts that are related to **sharing information** regarding the course, relevant publications, and other resources. These topics were indicative of weeks 1 to 3, as well as of weeks 7 and 11.
- The second group was based on topics related to **connectivism as a learning theory**. It is interesting to note that these topics were more frequent during the first four weeks of the course. Topics in this category included discussions on learning in networks (week 1); connectivism and its influence on instructional design (week 2); connectivism as one of the emerging learning theories (week 3); and unique characteristics of connectivism (week 4). Later in the course, topics such as connectivism as a learning pedagogy (week 8) received significant attention, as well as the potential influence of a connectivist approach to learning on changes in the role of instructional designers (week 9).
- The third group of topics was related to the application of **connectivism in practice**. The most notable points discussed included teaching foreign languages in connectivist settings and desirable competencies for teaching online (week 4); necessary skills for learning in networked learning environments (week 5); and the role of learners in connectivism and the importance of learning analytics (week 6). The topics belonging to this group received significant attention later in the course with the introduction of the concept “sharing for learning” in connectivism and available technologies for collaboration within a connectivist course (week 9). Finally, within the week 12 the role of connectivism in theory-informed research was also addressed.
- Within the fourth group of topics, **networked learning and establishing communities in networked learning environments** gained significant attention. Here, the course participants were interested in topics such as taking control of learning (weeks 2 and 3); networks and communities

emerging from MOOCs (week 3); collaboration within networked learning environments (weeks 8 and 10); and design and delivery of social networked learning (week 12).

- The final and the *largest set* of topics was primarily focused on **educational technology** and its application in various settings. The most indicative topics of this group are personal learning environments (weeks 5 and 6); social media in education (week 5); teaching with ICT and tools available (weeks 6 and 12); tools for learning and complex adaptive systems (week 7); integration of technological affordances into traditional classroom settings (week 8); challenges and best practices of educating teachers to use available technological affordances (week 9); and mobile (week 10) and blended learning (week 11).

Our analysis of topics detected in blog posts revealed topic groups similar to those observed in tweets, though with some observable differences:

- The first group of topics, similar to the one detected in Twitter messages, was about **sharing course resources**: information about the course and the readings (week 1), and the concept map of connectivism (week 11).
- The second group identified topics related to **MOOCs** in general: the concept of MOOC, previous MOOCs (e.g., PLENK, CCK08) (week 1), and how MOOCs affect learning in classroom settings (week 8). Although the topics from this group appeared throughout other weeks of the course, these topics were mostly discussed at the beginning of the course.
- The third group of topics received significant attention within the first five weeks of the course. This group was related to **connectivism as a learning theory**, and how connectivism relates to other learning theories. Course participants discussed the main characteristics of connectivism (weeks 1, 4, and 12) and relationships to other learning theories (week 5); validity of connectivism as a learning theory (week 2); teachers’ role in connectivism (weeks 3 and 8); aspects of teaching English as a foreign language in connectivist settings (week 5); and about collective intelligence, constructivism, subjectivism and importance of interpretation (weeks 5 and 10).

**Table 2. The number of exchanged posts and three most dominant topics (with the size as a percentage of all the clusters) for each week and each media; for each topic, the three most central concepts (sorted by betweenness and degree centrality) are given**

	Twitter	Blogs	Facebook
Week 1	Total Topics: 3 Total Posts:30 T1 (45%): concept, substantial form, social T2 (27%): knowledge, open source, e-learning T3 (27%): connectivism, video, constructivism (learning theory)	Total Topics: 7 Total Posts:200 T1 (67%): learning, education, knowledge T2 (19%): twitter, concept, teacher T3 ( 6%): tag, critical thinking, website	Total Topics: 5 Total Posts:84 T1 (36%): connectivism, idea, learning T2 (25%): facebook, open source, uploading and downloading T3 (18%): information, paradigm, twitter
Week 2	Total Topics: 7 Total Posts:270 T1 (33%): connectivism, education, e-learning T2 (22%): employment, social network, thought T3 (22%): learning, concept map, instructional design	Total Topics: 7 Total Posts:159 T1 (35%): learning, knowledge, thought T2 (18%): argument, research, computer network T3 (18%): motivation, facebook, MOOC	Total Topics: 11 Total Posts:260 T1 (17%): twitter, facebook, quora T2 (17%): learning, tradition, employment T3 (15%): education, connectivism, knowledge
Week 3	Total Topics: 6 Total Posts:256 T1 (30%): connectivism, wikipedia, conversation T2 (26%): learning, knowledge, computer network T3 (15%): education, e-learning, stephen downes	Total Topics: 8 Total Posts:145 T1 (19%): thought, knowledge, social network T2 (17%): teacher, connectivism, information T3 (17%): mind, writing, metaphor	Total Topics: 11 Total Posts:189 T1 (21%): learning, thought, connectivism T2 (16%): linkedin, facebook, social network T3 (11%): knowledge, idea, object (philosophy)
Week 4	Total Topics: 7 Total Posts:236 T1 (23%): connectivism, education, constructivism (learning theory) T2 (20%): e-learning, social network, actor?network theory T3 (17%): learning, information age, theory	Total Topics: 9 Total Posts:160 T1 (25%): connectivism, knowledge, social network T2 (24%): theory, technology, time T3 (22%): thought, learning, education	Total Topics: 9 Total Posts:210 T1 (18%): knowledge, connectivism, social change T2 (18%): thought, e-learning, student T3 (16%): learning, education, skill
Week 5	Total Topics: 6 Total Posts:271 T1 (36%): e-learning, connectivism, bonk (video game series) T2 (24%): edtech, internet, english as a foreign or second language T3 (17%): education, educational entertainment, teacher	Total Topics: 8 Total Posts:182 T1 (27%): thought, theory, truth T2 (20%): sound, youtube, human T3 (18%): education, learning, connectivism	Total Topics: 8 Total Posts:269 T1 (24%): thought, knowledge, understanding T2 (23%): learning, education, student T3 (22%): connectivism, wiki, facebook
Week 6	Total Topics: 4 Total Posts:217 T1 (37%): connectivism, english as a foreign or second language, behaviorism T2 (32%): education, edtech, e-learning T3 (21%): collaboration, knowledge, thought	Total Topics: 9 Total Posts:109 T1 (18%): learning, education, psychology T2 (17%): feedback, connectivism, cognition T3 (15%): theory, book, internet	Total Topics: 8 Total Posts:144 T1 (20%): learning, thought, history of personal learning environments T2 (18%): knowledge, information, brain T3 (17%): diigo, blogger (service), tool
Week 7	Total Topics: 6 Total Posts:270 T1 (42%): connectivism, twitter, knowledge T2 (24%): edtech, e-learning, mind map T3 (14%): technology, complex adaptive system, department of education and communities	Total Topics: 8 Total Posts:122 T1 (22%): learning, education, knowledge T2 (17%): sense, idea, intention T3 (14%): complexity, understanding, human	Total Topics: 6 Total Posts:73 T1 (23%): education, knowledge, culture T2 (20%): twitter, united kingdom, facebook T3 (18%): information, employment, history of personal learning environments
Week 8	Total Topics: 4 Total Posts:207 T1 (37%): connectivism, writing, book T2 (30%): education, e-learning, edtech T3 (17%): social network, learning, power (philosophy)	Total Topics: 4 Total Posts:71 T1 (69%): learning, social network, psychology T2 (27%): research, neoplatonism, people T3 ( 3%): massive open online course, internet forum, beauty	Total Topics: 7 Total Posts:94 T1 (20%): knowledge, intelligence, information technology T2 (17%): education, rss, plug-in (computing) T3 (17%): research, social media, new media
Week 9	Total Topics: 5 Total Posts:156 T1 (42%): edtech, e-learning, web 2.0 T2 (33%): internet, connectivism, file sharing T3 (11%): learning, school, control theory	Total Topics: 9 Total Posts:87 T1 (26%): learning, education, hypothesis T2 (22%): thought, social group, happiness T3 (13%): skill, knowledge, literacy	Total Topics: 5 Total Posts:132 T1 (26%): education, student, technology T2 (22%): connectivism, knowledge, connectionism T3 (21%): learning, thought, object (philosophy)
Week 10	Total Topics: 5 Total Posts:160 T1 (38%): connectivism, computer network, pedagogy T2 (21%): e-learning, education, teacher T3 (19%): learning, MOOC, google apps	Total Topics: 9 Total Posts:111 T1 (27%): learning, education, educational psychology T2 (13%): facebook, google, twitter T3 (12%): truth, metaphor, behaviorism	Total Topics: 9 Total Posts:113 T1 (28%): learning, thought, connectivism T2 (22%): employment, student, collaboration T3 (19%): book, writing, child
Week 11	Total Topics: 6 Total Posts:228 T1 (36%): connectivism, social media, emergence T2 (25%): e-learning, edtech, education T3 (14%): learning, theory, information age	Total Topics: 7 Total Posts:76 T1 (22%): education, teacher, pedagogy T2 (21%): learning, psychology, science T3 (20%): thought, skill, concept map	Total Topics: 5 Total Posts:50 T1 (32%): knowledge, learning, quality (philosophy) T2 (21%): connectivism, thought, behaviorism T3 (18%): value (personal and cultural), wisdom, truth
Week 12	Total Topics: 6 Total Posts:182 T1 (31%): connectivism, web 2.0, networked learning T2 (28%): e-learning, education, edtech T3 (17%): learning, english as a foreign or second language, information age	Total Topics: 6 Total Posts:51 T1 (26%): thought, pedagogy, connectivism T2 (24%): learning, observation, education T3 (18%): writing, memory, attention	Total Topics: 7 Total Posts:137 T1 (22%): learning, research, connectivism T2 (20%): google, writing, English language T3 (18%): person, applied science, education



- **Networked learning** and learning in connectivist settings received the highest attention among the course participants who were using blogs as a communication medium. The main topics covered included complexity of learning in networks, professional learning and importance of motivation for learning in networked environments (weeks 2, 4, 7 and 12); tools for learning in networks and gathering information (week 2); groups versus networks in connectivist settings (week 3); importance of interactions, internal and external feedback for learning in networks (weeks 6, 7, and 10); the source of knowledge/intelligence in networks (week 8); the role of technology in mediating teachers' role in networked learning (week 11), and learning affordances in networked learning environments (week 9); and digital literacy (week 9) and conceptual models for learning in networks (week 12);
- Discussions about **online and distance education** represent the fifth group of topics. The most commonly discussed topics included e-learning in classroom settings (week 3); social media services and social media platforms in online and distance education (weeks 5, 7, 8, and 10); social networks, social groups, and emerging social communities in distance education (weeks 6 and 9); instructional design for alternative education (weeks 9, 10, and 12), and metrics for measuring learners' success in online and distance education (week 10).
- The final group of topics was concerned with **educational technology** and use of ICT in education. Virtual learning environments and their use in higher education (weeks 6 and 7), ICT for teaching foreign language (week 7), personal learning environments (week 8) and learning management systems in education (weeks 11 and 12), were most commonly discussed in blog posts.

According to our analysis, learners' messages exchanged on Facebook remained within similar general topics:

- **Available resources** and information about the **course content** were common topics within weeks 1, 2, and 12.
- Within the **connectivism as a learning theory** topic group, the course participants were discussing the idea of connectivism and its position in education (weeks 1 and 2); how connectivism was different from the paradigm "wisdom of crowds", collective and connective wisdom (weeks 3 and 11); the main challenges of new learning theories (week 7); origins of connectivism (e.g., connectivism as a connectionist approach to learning) (week 9), and how connectivism empowers learners to take responsibility for their learning (week 11).
- Similar to blogs, **networked learning** and **learning in connectivist settings** received the most significant attention. These topics were evenly distributed throughout the course, and included networked learning and affordances that foster learning and help development of digital literacies (weeks 1 and 2); nature of teaching and learning in connectivism (weeks 4 and 8); social networking groups and sharing information within networks (weeks 3, 5, and 10); assessment in the connectivist framework (weeks 10 and 11); and collaboration and cooperation in networks (week 11).
- As with other media analyzed, **educational technology** was quite significant topic starting from the week four of the course. Institutions of higher education and their view of the role of ICT in education (week 4); social media platforms and connectivism (week 5); personal learning environments and differences/similarities with learning management systems (weeks 6 and 7); tools for collecting, sharing and tagging resources (week 6); role of educational technology in

teaching foreign languages (weeks 9 and 10); and ICT and intellectual ethics (week 8), were the most prominent.

- Opposite to blogs where topics about online and distance education were quite prominent, within the Facebook communication channel, topics on **education** in general received more attention. Course participants were interested in advantages and disadvantages of formal and institutional learning (weeks 4 and 7); the role of scholars in digital environments (week 2); how we learn and where we are learning from (week 3); important characteristics and skills of learners that drive learning in general, and in connectivist settings (week 5), how to create knowledge from information (week 6).

## 5. DISCUSSION

### 5.1 Interpretation of results with respect to the research questions

Considering the subject of the course, it is not surprising that the most common topics covered within each media are related to *connectivism as a learning theory*, *networked learning*, *education* (in general, and online and distance education in particular), *skills for teaching/learning in networks*, and *educational technology*. However, concepts discussed within each topic differ to a certain extent. For example, among topics related to educational technology that were discussed in blog and Facebook posts, there was a topic covering the issues of teaching and learning with ICT. While the course participants, who discussed this topic through blog posts, were mostly focused on technological affordances in teaching foreign language, posts exchanged on Facebook discussed the same topic from the learners' perspective.

Regarding our first research question (RQ1), we found that except for the first week of the course and concepts extracted from Twitter, the topics learners discussed in their posts in all three media analyzed tended to follow a similar pattern. In particular, posts tended to cover a wide set of concepts that quite differed from one post to another (Figure 2). However, our findings also indicate that concepts extracted from Twitter posts less frequently co-occurred and were less tightly coupled within a topic than in case of blog and Facebook posts (Figure 2 and 3). It could be deduced that blog and Facebook allowed for writing more coherent posts. This confirms previous findings that social media vary in their affordances [40], in terms that certain social platforms allow for more elaborate writing on topics of interest. On the other hand, less coherent discourse might be an indicator of difficulties to form a learning community. Without a clear set of shared interest, it is unlikely that a community would emerge. Observing though the perspective of the three media analyzed, it seems that blogs and Facebook offer better opportunities for the community development.

As for our second research question (RQ2), we found that posts throughout the 12 weeks of the course mostly covered topics from recommended readings for the first three weeks. Within those three weeks of the course, readings included topics such as *connectivism as a learning theory*, *learning in networks*, as well as *learning in networks and connective knowledge*, which we identified as the most common topics in the analyzed posts. Moreover, Figure 5 shows that topics discussed within two consecutive weeks did not differ significantly, indicating that course participants tended to continue conversation on the topic of interest, rather than follow new themes introduced within the course. This suggests that those dominant themes are determined by groups of learners who engage collaboratively, rather than by the instructor. Therefore, we might conclude that our results support the main theoretical assumptions of connectivism [1] and are in line with the previous studies [8, 27]. More precisely, the

learning process is not focused on transferring knowledge from the instructor to course participants, but rather on the connections and collaboration between learners [6], while learners also participate in content creation. Moreover Kop, et al. [15] and Skrypyk et al. [27] confirmed that the information flow and knowledge building process also depend on those network-directed learners who are willing to engage into interaction with their peers and share knowledge among the network of learners. Therefore, it seems reasonable to conclude that learners engage into discussions with peers who share similar interests, thus framing the topics discussed within each media.

Finally, regarding our third research question (RQ3), our findings show that even though the count of topics identified within each week changed over time and differed among the media analyzed (Figure 1), the most dominant and high-level groups of topics (e.g., educational technology, networked learning) quickly emerged, and sustained throughout the course. More specialized concepts did change in each group of topic, since learners showed interests in various aspects of those topics (e.g., social network analysis, personal learning environments). However, overall they remained focused on the general groups of topics.

## 5.2 Limitations of this study

In order to address issues of internal and external validity of our findings, certain limitations need to be acknowledged. The main issues regarding internal validity originate in the process of data collection and concept extraction. In our study, we relied on gRSShopper for the automated collection of learners' blog posts, and copies of tweets. This source was used as by the time we collected data for the study (April-August 2014), several blogs were not available any longer. Likewise, due to the limitations introduced by the Twitter API, we were not able to obtain original tweets. Therefore, we turned to the posts available within the CCK11 newsletter. Second, we relied on Alchemy API and TagMe for the extraction of concepts from learners' posts and recommended readings. However, as stated in the Methodology section, these tools produced some erroneous concepts that we manually removed. This suggests that the extracted concepts might not fully and correctly represent the themes discussed in posts and readings. Finally, we relied on Microsoft Translate API in order to translate non-English posts (5% of all the collected posts), therefore the resulting translations depend on the quality of the API used.

Addressing issues of external validity is important from the perspective of generalizing our findings. Therefore, it is important to conduct a similar analysis within a different educational domain or course.

## 6. CONCLUSIONS

The reported study proposed a novel analytic approach that integrates tools and techniques for automated content analysis and SNA with qualitative content analysis. This approach was used for the exploration of topics emerging from the learners' discourse in cMOOCs, and offered an in-depth insight into the topics being discussed among course participants. Moreover, the proposed analytic method also allowed for validation of certain ideas of connectivism – e.g., learners were primarily focused on the course topics they were interested in, regardless of the topics suggested by the course facilitators, while the technology had a significant impact on how learners discussed certain topics [6]. Further, our approach might be suitable for analysis of different media used in cMOOCs, as one of the critical features. For such multi-media studies, it is essential to proceed to the analysis of actual content and discourse rather than just counts of the use (e.g., page hits) [41, 42]. This is necessary as different media have different

affordances that can affect how processes of knowledge creation unfold in cMOOCs [18, 26].

Building a trustworthy community in diverse and large networks, as those emerging from cMOOCs, is recognized as one of the important challenges [26]. Being able to reveal topics discussed in different media and among emerging social groups might help learners to “bridge the social gap” and more easily reach groups with similar interests. On the other hand, our study also shows an overall low density of the analyzed concept graphs. This might be an indicator of low cohesion among the concepts used by learners [38], and low-to-moderate mutual understanding and consensus built within the entire network [37]. It seems that, at the network level, course participants could not find shared concepts of interests within those broader topics being discussed. In addition, our findings might indicate a lack of shared vocabulary or conceptual models, considering that people originated from different backgrounds and different cultures. However, a broad consensus of the entire network – per medium – might not be possible given the size and diversity in interests, background, and goals of the course participants. Perhaps, a better unit of analysis could be communities. For example, further research should create similar graphs for specific communities – e.g., such as those that emerged in the study reported in [27] – and analyze their cohesion, rather than the cohesion of the entire network. We would expect to reveal higher graph density, and more connected graphs, as indicators of higher level of shared understanding.

Our findings also indicate that several topics gained significant attention, while other course topics were not commonly discussed among learners. Therefore, the question is how facilitators and/or learners should proceed with regard to those less “interesting” topics? Given that learners choose what to learn in cMOOCs, should facilitators provide a better connection with those topics that were “more popular”, or introduce “less popular” topics in different ways, or perhaps such findings could inform the course design, pointing out to the most important topics for the course participants?

Further research is also needed to examine how different social groups shape discussions and whether we can identify certain patterns in learners' approaches to course-related discussions, over various social media. For example, it would be interesting to analyze how social groups formed around certain topics evolve over time; are there groups that use various media to collaborate with their peers on a certain topic; and how much attention receive topics initiated by course facilitators, compared to topics proposed by learners.

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### 5.3 Publication: Analyzing complex interrelationship between discourse, structure, and dynamics

The following section includes the copy of the following publication that was submitted for the review:

[Joksimović, S.](#), Jovanović, J., Kovanović, V., Gašević, D., Milikić, N., Zouaq, A., and van Saalduinen, J.-P. (2017, *under review*). Comprehensive analysis of discussion forum participation: from speech acts to discussion dynamics and course outcomes. *Computers in Human Behavior*

# Comprehensive analysis of discussion forum participation: from speech acts to discussion dynamics and course outcomes

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## Abstract

Learning in digitally connected, computer-mediated settings represents a complex, multidimensional process. This complexity calls for a comprehensive analytical approach that would allow for understanding of various dimensions of learner generated discourse and the structure of the underlying social interactions. Therefore, in this study we posit that discourse and social network analyses should be applied as complementary approaches, rather than independent analytical methods. From the perspective of discourse analysis, we propose an analytical approach that employs an unsupervised method for identification of speech acts expressed in online discourse and allows for exploring sequences of speech acts employed in communication. We were able to extract six categories of speech acts from messages exchanged in discussion forums of two studies MOOCs: *Directive speech acts* (questions & answers, instruction, and elaboration), *Expressives*, *Representatives*, and a category of messages that could not be characterized as any act of speech, and thus was labeled *Other*. We further showed how different conversational patterns evident in the students' contributions to discussion forums revealed rather distinct social dynamics that framed emerging social networks. Complementing the discourse analysis with the methods of statistical network analysis, we were able to interpret an association that social centrality and forum participation have with the final course outcome. Finally, the study discusses potential implications for research and practice.

*Keywords:* Speech acts, social networks, learning outcome, statistical network analysis, discourse analysis

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## 1. Introduction

Learning in digital learning environments presents a complex phenomenon, framed by social interactions that occur in the given learning settings and available technological affordances that support individual and collaborative learning activities (Goodyear, 2004; Jones, 2015; Ohlsson, 1996).

The sociocultural perspective of learning, primarily based on Vygotsky's (1986) understanding of human learning and development, highlights the importance of social interaction and collaborative learning for creating effective environments that support knowledge construction (Jones, 2015; Stahl, 2007; Warschauer, 1997). Knowledge building and information sharing in digitally connected learning contexts primarily occur through language and discourse (Jones, 2015; Stahl, 2004). In this paper, we argue that studying learning in digitally connected, computer-mediated settings, as a multidimensional process, needs to account for understanding of a) discourse produced (Halatchliyski, Moskaliuk, Kimmerle, & Cress, 2014; Jones, 2015), and b) social structures emerging from interactions in digital learning environments (Goodyear, 2004; Jones, 2015).

In a broader context of computer supported collaborative learning, the literature recognizes various approaches to the study of collaborative discourse. Stahl (2003), for example, focuses on analyzing *meaning* as a “shared, collaborative, interactive achievement” (*ibid.*, p.10) expressed in discourse generated in the process of knowledge construction. Every “artifact, action, word or utterance” (Strijbos, Kirschner, & Martens, 2006, p. 71), Stahl contends, obtains a meaning from its position in a sequence of interactions (Stahl, 2003). In online educational settings, where student generated discourse presents primary means of social interaction, understanding cognitive actions in terms of intentions, purpose or effect expressed in communication, is perhaps of utmost importance when studying collaborative discourse (Jones, 2008). Speech act theory provides a comprehensive framework for studying knowledge construction through computer-mediated communication. Speech acts theory, provides a comprehensive framework that observes communication utterances as being beyond “mere meaning-bearers, but rather in a very real sense do things, that is, perform actions” (Levinson, 2017, p. 1), such as thanking, apologizing, and asking questions. As such, speech acts theory provides insights into the *intended* meaning of a communication act and the extent of shared understanding between peers participating in a communication (Bazerman, 2004; Searle, 1976; Stahl, 2003).

Discourse, however, is not an isolated process but one that emerges from the interaction among actors in a given educational context (Goodyear, 2004; Jørgensen & Phillips, 2002; Marbouti & Wise, 2016). Moreover, discourse is “constantly being transformed through contact with other discourses” (Jørgensen & Phillips, 2002, p. 6). This further implies that the student-generated content should be observed as inherently social, whereas the meaning of discourse could be operationalized only through the social adoption (Bakhtin, 1986; D. Hicks, 1995; Stahl, 2004; Vygotsky, 1986). Therefore, observing discourse properties without accounting for the context of the underlying social interaction (e.g., who is talking with whom) could be potentially misleading in explaining learning in technology mediated settings (Joksimović et al., 2016).

Social network analysis (SNA) has been commonly applied in examining student interactions emerging from learning in digital educational settings (Carolan, 2014). Shifting the focus of analysis from the individual level to the group level, SNA enables accounting for the importance of group dynamics, and provides comprehensive insights into the quantity and quality of social interactions within a given networked context (Cela, Sicilia, & Sánchez, 2015; Kellogg, Booth, & Oliver, 2014; Skrypnik, Joksimović, Kovanović, Gasšević, & Dawson, 2015). Besides the use of descriptive methods and analysis of network structural and generative properties (e.g., centrality, density, triad closure) (Stepanyan, Borau, & Ullrich, 2010; Vaquero & Cebrian, 2013), recent research also offers methods to explain the social dynamic processes (e.g., tendency to form reciprocal or homophilic ties) that drive network formation (Joksimović et al., 2016; Poquet & Dawson, 2016; Zhu et al., 2016). Although social network indicators allow for revealing emerging roles and structure of interactions in learning networks, SNA alone is not sufficient for deeply understanding patterns of interactions in a given learning environment. For example, the dynamics that affect tie formation, one also needs to account for the specificities of the discourse generated through student communication.

To provide a comprehensive understanding of different facets of learning in digital learning environments, we posit that discourse and social network analysis should be applied as complementary approaches, rather than independent analytical models (De Laat, 2006; Gruz, Haythornthwaite, Paulin, Absar, & Huggett, 2014; Jones, 2008; Oshima, Oshima, & Matsuzawa, 2012). It is important to note that the literature recognizes similar attempts to make a connection between the two analytical methods. For example, De Laat (2006) utilizes SNA to reveal most influential discussion participants in learning activities and to explain overall patterns of connections between peers. De Laat (2006) further applies qualitative coding scheme for analyzing negotiation of meaning and social construction of knowledge in computer-mediated interaction. Although very beneficial for understanding learning in computer-mediated settings, such approach is primarily based on the interpretation of the eventual association between discourse and descriptive network properties. De Laat's (2006) analytical approach does not necessarily establish inferential links between the complementary perspectives (discourse and social structures), thus lacking capacity to explain how actions expressed through discourse frame social interactions observed in a given context. Moreover, De Laat (2006) does not necessarily accounts for the sequence of indicators of knowledge construction that, according to Stahl (2003, 2004) and Molenaar and Chiu (2015) among others, provides a basis for understanding the process of knowledge construction. Finally, being primarily based in manual analysis methods, it is questionable to what extent the analytical approach proposed by De Laat (2006) is scalable.

Considering all the above, this study focuses on several objectives. First, we employ an unsupervised method for the identification of speech acts as a way for understanding intended

meaning of communication acts, expressed in discussion forums of online courses. Unsupervised approach allows for analyzing student interactions at scale by overcoming the limitations of manual coding (supervised methods require coded datasets). Further, we also examine conversation dynamics of student discussions to provide a more comprehensive understanding of sequence of actions employed in communication; this is one of the most prominent ways for reflecting the structure and the process of collaborative knowledge construction (Stahl, 2004). Moreover, we explore how student generated discourse shapes social interactions in learning networks, and thus provide an inferential association between metrics observed through discourse analysis on the one hand, and SNA on the other hand. Finally, we examine to what extent the detected patterns of association between discourse and structure of social interactions provide a context for interpreting factors that influence student learning outcomes.

## **2. Background**

### *2.1. Speech Acts Theory at a Glance*

Student generated discourse represents one of the richest sources of information about student learning (Azevedo, 2015). In addition to self-reports, discourse produced in student interactions represents the only source for obtaining insights into the cognitive, metacognitive, affective, and motivational dimensions of student engagement (Azevedo, 2015; Gašević, Dawson, Rogers, & Gasevic, 2016). However, student discussions should be observed as being “embedded within structured social activities” (Bazerman, 2004, p. 311), and as such, dependent on previously generated content that influences social interactions in a given context. Each artefact (piece of text, more specifically) generated by a student or a teacher, creates a social fact for all the participants in the interaction (Bazerman, 2004). As further posited by (Bazerman, 2004), social facts are usually comprised of speech acts – utterances considered as an action, particularly about their intention, purpose, or effect (Levinson, 2017; Searle, 1976). Therefore, discourse analysis, should also investigate the meaning and intended actions (e.g., asking questions, thanking, or apologizing) of any utterance used in a communication (Arguello & Shaffer, 2015; Austin, 1962; Azevedo, 2015; Bazerman, 2004).

Being rooted in sociolinguistic and philosophy research, speech act theory allows for departing from analyzing the structure of student discourse to account for the particular purpose the exchanged textual content has in a social interaction (Arguello & Shaffer, 2015; Bazerman, 2004). Although there have been various attempts to classify speech acts, the most general classifications have been provided in Austin (1962) and Searle's (1976) seminal works on speech act categorization based on illocutionary acts. Specifically, both Austin and Searle argue that speech acts operate on three levels:



i) locutionary (propositional) act represents the main message, that is, “what is being said” (Bazerman, 2004, p. 314), ii) illocutionary act expresses the intended act the speaker wanted to accomplish, and iii) perlocutionary act (effect) that explains how specific act was understood by other participants in communication and what are potential consequences of the act (Austin, 1962; Bazerman, 2004). Both categorizations, therefore, observe illocutionary act, or intended purpose, as a “basic unit of human linguistic communication” (Searle, 1976, p. 1). Of special interest for this study is Searle’s categorization of speech acts, as it is arguably the most general classification of illocutionary acts, as well as a refined conceptualization of Austin’s work. Observed through the three critical dimensions, *illocutionary point*, *direction of fit*, and *sincerity condition of the act*, Searle defined the classification that includes the following speech act categories: *representatives*, *directives*, *commissives*, *expressives*, and *declarations*.

As originally defined in Searle’s work, the purpose of the *representative* category of speech acts is to “commit the speaker (in varying degrees) to something’s being the case” (Searle, 1976, p. 10). That is, utterances that belong to the *representative* class depict the speaker’s belief that could be assessed either as true or false. *Directives*, on the other hand, represent speech acts that point to the speaker’s expectations that the listener performs certain action. Directive, therefore, could be stated in a form of invite, permit, advise, request, command, or question, to name a few (Searle, 1976). *Commissives* are defined as a category of speech acts that commits the *speaker* to perform certain action, such as promises, or threats. The main intent of *expressive* speech acts is to communicate the speaker’s psychological state about the specific “state of affairs specified in the propositional content” (Searle, 1976, p. 12). Examples include expressions of gratitude, apologizes or welcoming (Levinson, 2017; Qadir & Riloff, 2011; Searle, 1976). Finally, *declarative* speech acts are characterized by implying certain alteration “in the status of condition of the referred-to object”(Searle, 1976, p. 14).

## 2.2. Meaningful Social Actions and Learning

In the context of analyzing student interaction in online learning settings, speech acts have been commonly used in summarizing discussion threads (Bhatia, Biyani, & Mitra, 2014) or in investigating student participation patterns and predicting learning outcomes (Arguello & Shaffer, 2015; Merceron, 2014). For example, Merceron (2014) relied on the speech act theory to examine what role student messages have in discussion forums and to what extent the message posting patterns (i.e., number of messages belonging to each of the speech act categories) differ between high and low performing students. The focus of the analysis in Merceron's (2014) study was on the data obtained from a traditional online (for credit) computer science course. Merceron manually coded student discussion forum posts according to the categories proposed by Kim, Li, and Kim (2010), which include *questions*, *issues*, *answers*, *positive acknowledgments*, *negative acknowledgments*, and *references*.

Merceron (2014), as well as Kim and colleagues (2010), among others, relied on more domain specific categories of speech acts, derived from broad categorizations introduced by Austin (1962) and Searle (1976). The study revealed that the more successful students tend to be more focused on providing help to their peers and answering questions, whereas student who obtained lower grades, were oriented towards help-seeking. However, there was no association between the forum participation and performance for the high performing students.

Perhaps the most relevant for our research is Arguello and Shaffer's (2015) work on automated prediction of speech acts in discussion forums of a massive open online course (MOOC) and examining the association between the course performance and particular acts of speech. Similar to the work of Merceron (2014) and Kim et al., (2010), Arguello and Shaffer (2015) also observed *questions, answers, issues, positive and negative acknowledgements*. However, Arguello and Shaffer (2015) further included the *issue resolution* and *other* speech acts. Arguello and Shaffer (2015) revealed that students raising issues were more likely to successfully complete a course and to submit an assignment. However, their models for predicting assignment completion and course performance explained only a very small amount of variance (4.2% and 1.7%, respectively, using Nagelkerke's  $R^2$ ).

The existing research, thus, provides evidence for the association between different categories of speech acts (i.e., the purpose a particular message has in a discussion forum) and a learning outcome. However, there seems to exist an evident gap in the literature where existing research fails to provide a holistic understanding of the association between discourse properties and underlying social processes that frame peer interaction. That is, although literature recognizes the importance of analyzing speech acts in order to understand knowledge building processes, there seems to be a lack of studies exploring particular ways in which acts of speech have been employed in communication (Stahl, 2004). Moreover, it is not clear whether and to what extent the utilization of specific categories of speech acts influences development of social ties in an emerging social network (Joksimović et al., 2016). Finally, the question remains whether patterns of social interactions provide a salient context for interpreting the association between students' social activity and final learning outcome.

### 2.3. Social Network Analysis

Social Network Analysis (SNA) is a methodology that allows for examining patterns of human interaction in diverse social settings (Freeman, 1978; Wasserman, 1994). Shifting the focus from observing individual attributes of participants in social interactions to the analysis of social groups, SNA looks at how individuals life, work or study depends on social connections they are tied to (Carolan, 2014). SNA has played a prominent role in learning sciences, providing theoretical and methodological tools for understanding activities and social processes that students and teachers engage with (Carolan, 2014; Stepanyan et al., 2010).

### ***Networks centrality and learning outcome***

In the context of educational research, and MOOCs in particular, SNA has been commonly applied to examine whether and how structural properties of networks (e.g., degree or betweenness centrality) are associated with learning, creative potential, sense of community or educational experience in general (Dawson, 2008; Freeman, 1978; Granovetter, 1973; Wasserman, 1994). A prevailing understanding emerging from the existing SNA literature, is that a high centrality in a social network implies more benefits – e.g., a higher degree or betweenness centrality is often associated with a higher course grade. However, certain inconsistencies with respect to the existing results are also evident. For example, while Jiang, Fitzhugh, and Warschauer (2014) provided an evidence for the significant and positive association between social centrality (degree and betweenness in this case) and learning outcome (i.e., course grade), studies by Cho, Gay, Davidson, and Ingraffea (2007) and Gašević, Zouaq, and Janzen (2013) did not support those findings.

Analyzing this issue, Joksimović and colleagues (2016) posited that potential reason for contradictory findings with respect to the importance of the student social centrality might originate in the social dynamic processes that drive network formation. Specifically, in the study conducted in the context of a MOOC, Joksimović and his colleagues (2016) empirically showed that the networks built primarily on *super strong* ties (Krackhardt, 1999; Simmel, 1950) – i.e., “those having a high probability of being real and intimate friendships” (Pappalardo, Rossetti, & Pedreschi, 2012, p. 1043) – are unlikely to offer benefits to centrally positioned nodes. Rather, those benefits are afforded in networks that are primarily formed on weak ties as consistent with the social network literature (Krackhardt, 1999).

### ***Exploring factors of network formation***

As one of the emerging methods in educational research, statistical network analysis is gaining increasing attention in studying regularities of student participation in MOOCs. For example, Kellogg and colleagues (Kellogg et al., 2014) aimed at understanding social processes arising from interactions in a network of educational professionals. Accounting for various patterns of selective mixing and network statistics (e.g., reciprocity, homophily by professional role, gender, or educational background), Kellogg et al.'s (2014) study showed a strong and significant tendency for students to reply to a peer when there has been prior evidence of reciprocity. Homophilic and heterophilic effects, on the other hand, as well as proximity mechanisms differed across the networks analyzed. Likewise, Poquet and Dawson (2016) showed that conversational patterns (e.g., cognitive or socio-emotional) and participation regularity had a significant effect on how social processes unfold at scale. Zhu et al. (2016) adopted a slightly different approach, analyzing social interactions on a weekly basis.

Although individuals with higher performance scores tended to have more social ties, Zhu et al. (2016), did not find any evidence of the preferential attachment effect.

One of the objectives of our study is to examine whether social network characteristics (e.g., tendency to form reciprocal or homophilic ties) provide a salient context for understanding factors that are associated with learning outcomes. Specifically, applying social network analysis using exponential random graph models (ERGMs), we examine if students' discussion contributions tend to frame the underlying network formation. Here, we are particularly interested in tendency to form "super-strong" ties (Krackhardt, 1999; Simmel, 1950). The existence of this type of connections between forum participants is expected to affect the association between social centrality (i.e., degree, closeness, and betweenness) and learning outcome (i.e., final course grade).

#### *2.4. Research questions*

Aiming to understand factors that frame collaborative dialog among participants in discussion forums, we examine the intended meaning of student messages expressed through different speech acts. Here, we utilize automated methods for speech acts extraction from discussion forum messages, to provide means for large scale data analysis in online learning. Hence, we define our first research question as follows:

**RQ1.** *What kinds of speech acts are typically used by discussion forum participants in online learning settings?*

In addition to understanding meaning of students' contribution in collaborative knowledge creation, it is also important to understand sequence of speech acts occurrences (Marbouti & Wise, 2016; Stahl, 2004). Studying student messages in MOOC discussion forums, Gillani and Eynon (2014) and Poquet and Dawson (2016), among others, suggest the importance of understanding ways students interact in terms of the nature of the content they share or topics they participate in, as means for understanding the structure of the process of knowledge building. In this study, therefore, we aim at further investigating student participation patterns in terms of frequency of posting messages with a particular speech act, as well as the coherency of discussion threads (i.e., to what extent discussion threads transition from one speech act to another). Thus, we define our second research question as follows:

**RQ2.** *What patterns can be identified in the conversation dynamics (i.e., a sequence of speech acts) generated by students during their participation in a discussion forum?*

In addition to representing a primary form of students' projection in a digital educational environment and potentially valuable learning resources for their peers (Goodyear, 2004; Herring,

2001; Jones, 2008) student generated discourse also implies certain actions, and points to various activities or attitudes (Bazerman, 2004). This research, therefore, aims at further examining the association between student messages and processes that frame social interactions in learning networks. Specifically, by complementing a discourse analysis with methods and approaches of social network analysis, we aim to examine to what extent the intended meaning of student generated messages, observed through speech acts used in a discussion forum, reflect latent regularities that drive social network formation. Hence, we define the following research question:

**RQ3.** *To what extent can conversation dynamics, defined through emerging speech acts, explain social processes evident in social networks that emerge from student interactions in a discussion forum?*

Finally, in a recent study that examined factors affecting the association between the learning outcome and specific contextual factors, Joksimović and colleagues (2016) highlighted the importance of considering network characteristics when examining factors that might help with predicting learning. Specifically, by analyzing social networks emerging from MOOC interactions, Joksimović and colleagues (2016) showed how differences in social dynamics that frame social interactions affect the interpretation of variances in the predictive power of social centrality measures (i.e., degree, closeness, and betweenness centrality) on the final course outcome (i.e., obtained certificate). Therefore, we further aim at examining to what extent the characteristics of social processes that students participate in provide a context for interpreting the association between discussion forum activities (observed through the conversation patterns and social positioning) and final course grade. Therefore, we define our fourth research question as follows:

**RQ4.** *To what extent can factors that characterize student social interaction in a discussion forum provide a framework for interpreting the association between learning-related social constructs - namely conversation dynamics and social positioning - and learning outcome?*

### **3. Method**

#### *3.1. Data*

This study analyzes forum discussions within two MOOCs delivered by Delft University of Technology in 2014, using the edX platform. The courses included video lectures, quizzes, and assignments delivered across several modules, with a new module released every week. In both courses, students were required to score at least 60% in order to pass the course and obtain a certificate. With respect to discussion participation, neither of the courses counted discussion forum

participation towards the final grade. No particular guidance was provided for forum participation and forums in both courses were primarily structured as standard Q&A forums. The role of the teaching staff was primarily focused on moderating the discussion forum and replying to the students' questions. We focused our analysis on these two courses not only for their considerable difference with respect to the subject domains (i.e., industrial design and software engineering), but also for the significant differences in student completion rates. Although comparable percentage of enrolled students engaged with the course content, the numbers of students who obtained the certificate in the two courses were considerably different (Table 1).

The *Delft Design Approach* (DDA) course aimed at introducing the key elements, tools, and methods of the product and industrial design approach as taught at Delft University of Technology. During the course, students were taken through the complete product design process, starting with the early stages of framing ideas, to implementation and testing phases. Students were also able to compare their performance and designs to a set of performance benchmarks created by the course staff. The course was delivered over ten weeks with a planned study load approximately six to eight hours per week. Each video lecture was followed by a quiz, where quizzes, in total, accounted for 10% of the final grade. The course also included a peer-reviewed design exercise and a final presentation that counted 70 and 20 percent towards the final course grade, respectively. Through the peer-review process, students were expected to reflect on and discuss their work and the work of their peers within the course discussion forum.

TABLE 1  
DESCRIPTIVE STATISTICS FOR THE NUMBER OF ENROLLED STUDENTS, STUDENTS ENGAGED WITH THE COURSE CONTENT AND DISCUSSION FORUM, AS WELL AS THE OBTAINED CERTIFICATES

		Statistics	DDA	FP
Overall	Students	Enrolled	13,503	38,029
		Engaged*	6,604	22,673
		Forum part.	730 (11%)**	1,067 (5%)**
Discussion Participation	Threads	AVG (SD)	1.478 (1.162)	2.094 (3.198)
		Total	643	1,288
	Posts	AVG (SD)	3.921 (11.585)	7.714 (42.156)
		Total	1,886	6,904
	Contrib.	AVG (SD)	3.436 (10.048)	7.678 (39.422)
		Total	2,598	8,192
Obtained Certificates		Total	136 (2%)*	1,968 (9%)*

*Note: \* Engaged are those students who performed at least one activity (e.g., viewing a video, posting to discussion forum), in addition to being simply enrolled in a course; \*\* the number in parenthesis represents the percentage of engaged students.*

*Introduction to Functional Programming* (FP) focused on introducing fundamentals of functional programming using the Haskell programming language. Although the course did not assume prior knowledge of functional programming, at least one year of practice in programming languages such as Java or PHP was recommended. The duration of the course was slightly shorter than DDA (i.e., eight weeks) with four to six hours of estimated workload per week. The course included two types of assignments – homework (eleven in total) and lab assignments (seven in total), that counted towards the final grade. None of the assignments was optional and only one attempt was available per assignment.

### 3.2. Analysis

To address the **first two research questions**, we adopted unsupervised conversation modeling techniques for identification of different speech act categories that students used in their discussion messages. Most approaches for automated speech acts classification require manually coded student messages (Arguello & Shaffer, 2015). Such manual coding is a time-consuming process that requires considerable expertise and usually includes two or more expert coders (Krippendorff, 2012). The unsupervised method used in this study consists of clustering written utterances based on the similarity of the underlying conversational roles and does not require previously labeled data (Ritter, Cherry, & Dolan, 2010). Specifically, we relied on the approach proposed by Ritter and colleagues (2010) and later implemented and extended by Paul (2012). To identify different speech acts, the approach combines hidden Markov models (HMM) and Latent Dirichlet Allocation (LDA) (Blei, Ng, & Jordan, 2003). First, LDA topic modeling is used to extract speech acts (as LDA topics) from student discussion posts; then HMM estimates the probabilities of transitioning from one speech act to another (each speech act is a state in the HMM). The algorithm, named *block HMM*, assigns a state (i.e., speech act) to each message in a discussion forum. It should be noted that our approach focuses at a message as the unit of analysis, rather than an utterance, and a message could have more than one speech act. In that, our approach is similar to those used by Merceron (2014) and Arguello and Shaffer (2015) who also analyzed the role that “messages play in building understanding and knowledge” (Merceron, 2014, p. 12).

The underlying topic modeling algorithm (i.e., LDA), used in the Paul's (2012) implementation of block HMM, is a probabilistic technique, commonly applied in social sciences and humanities (D. J. Cohen et al., 2012), that allows for the extraction of prominent themes from a collection of text documents. By examining the co-occurrence of words in a document corpus, LDA identifies groups of words that are commonly used together and could potentially represent different themes across the corpus.

Although LDA can automatically detect important topics in a corpus, the algorithm must be provided with the number of topics to be identified. We opted for a model with six topics, since we focused our analysis on the five speech acts defined in Searle's (1976) categorization (*representatives*, *directives*, *commissives*, *expressives*, and *declarations*), and also recognized a need for the "other" category that captures the utterances lacking any speech act (Arguello & Shaffer, 2015; Qadir & Riloff, 2011). This solution was further confirmed using data-driven methods for identifying optimal number of topics, implemented in *ldatuning* R-package (Nikita, 2016). Specifically, using metrics proposed by Cao, Xia, Li, Zhang, and Tang (2009) and Deveaud, SanJuan, and Bellot (2014), the algorithm resulted in five to eight topics as optimal numbers for both datasets. Finally, after the investigation of the proposed solutions (i.e., exploring to what extent different topics actually represent distinct groups of speech acts), we decided to use six topics (i.e., HMM states) as the optimal number for both datasets.

In order to improve the estimation of word co-occurrences, LDA is often preceded by several pre-processing steps. Those include 1) the removal of "non-informative" tokens, such as highly frequent words that do not bear meaning by themselves (known as stopwords, e.g., 'a' and 'the'), punctuation, and very short words; and 2) lemmatization, that is, conversion of words to their root form (e.g., "gone" and "went" to the base form "go"). However, given that in conversational modeling some of the token categories that are typically removed (e.g., punctuations, numbers) can potentially indicate different speech acts (Paul, 2012; Ritter et al., 2010), in our analysis we decided to keep all the word categories.

To address specifically our second research question, we examined sequences of specific speech acts, as means of explaining emerging communication patterns and exploring the structure and the process of knowledge construction (Stahl, 2004), as well as discourse coherence (Marbouti & Wise, 2016). Specifically, the applied discourse analysis method – i.e., block HMMs (Paul, 2012; Ritter et al., 2010) - allowed us to generate a matrix of transition probabilities between speech acts employed in a conversation. As such, the employed method allowed for moving beyond simply exploring the speech acts that students commonly rely on in the process of knowledge building, and towards examining how sequences of interactions start and what patterns of transitions between different speech acts were. We further relied on transition counts – i.e., the numbers of transitions between different speech acts – to examine the association between conversation dynamics and learning outcome (Section 3.3.2). Moreover, like Gillani and Eynon (2014), we also computed how similar students were with respect to the number of posts in different pairs of speech act categories (e.g., the frequency of posting Directives Q&A and Expressives), analyzing thus the extent of discourse coherence and shared understanding between the course participants (Marbouti & Wise, 2016; Stahl, 2007). Similarity is computed using the Jaccard similarity metric, which measures similarity of two



vectors (W. Cohen, Ravikumar, & Fienberg, 2003). In our case, we calculated pairwise similarities between vectors representing students who posted within a particular category of speech acts.

### *3.3. Social Network and Statistical Analysis*

In order to explore social dynamic processes (and address the third research question) and investigate association between social positioning and learning outcome (and address RQ4), we extracted two directed weighted graphs that reflect interactions occurring within discussion forums of the two course instances (DDA and FP). We relied on the most commonly applied approach to extracting social networks from discussion forum interactions, which considers each message as being directed to the previous one in the thread (Joksimović et al., 2016). This approach tends to capture post-reply structure within discussion forum threads, by including directed edges between those students who replied to a specific post and the author of the post. In case certain interaction occurred more than once (e.g., author A2 replied to two posts created by author A1), we would increase the weight of the corresponding edge. Social graphs included all the students who posted to discussion forums.

#### *Exploring social dynamic processes*

Our **third research question** required an approach that would allow for examining determinants that define network formation evident in the analyzed social networks. Specifically, in order to complement discourse analysis and explore the association between conversation dynamics and social network formation processes (RQ3), we utilized statistical network analysis. Similar to the work by Joksimović and colleagues (2016), here we also relied on the exponential random graph models (ERGMs) – a family of statistical models for studying social networks (Goodreau, Kitts, & Morris, 2009). To investigate the association between conversation patterns and processes that drive formation of social networks, when fitting ERGMs, we accounted for two variables extracted from the online forum participation. Specifically, we included the number of posts submitted by each student and the number of transitions between different speech acts for each student, to account for the overall student activity and to capture the student's communication patterns (as addressed in RQ2), respectively. Those two participation-related metrics were included in the statistical model as main effects on the propensity to form ties.

Exploring further to what extent factors that drive network formation are framed by potentially different conversational dynamics, we relied on commonly used network statistics (Goodreau et al., 2009; Kellogg et al., 2014; Poquet & Dawson, 2016). Observing network statistics at the dyadic level, we aimed to investigate the effects of selective mixing (based on student achievement level),

reciprocity, popularity spread, and expansiveness (i.e., activity spread). Likewise, at the triadic level, we primarily focused on examining effects of transitivity and Simmelian ties formation.

Selective mixing is a network statistic that reflects the tendency of creating edges between nodes having the same characteristics (Goodreau et al., 2009). Specifically, we examined to what extent students with the same achievement level (i.e., passed or failed the course) were more likely to reply to each other's posts. Although we modeled selective mixing based on the student achievement in both courses, effects that yielded better fit in the observed networks slightly differed (Table 4). Specifically, for the social network extracted from the DDA course, we modeled *differential homophily* (i.e., preference for students who obtained a certificate to create ties with other students who obtained a certificate, and vice versa) (Goodreau et al., 2009; Lusher, Koskinen, & Robins, 2012), whereas in case of the FP course we managed to fit *uniform homophily* (i.e., propensity to form ties based on the achievement in general) for the same attribute. Initially, we aimed at investigating differential homophily in both courses. However, in the case of the FP course such configuration yielded worse model fit. Further, students' tendency to form mutual (i.e., reciprocal) ties and to cluster together was captured by the reciprocity network statistics (Lusher et al., 2012). By including the reciprocity in our models, we aimed at revealing students' tendency to continue interaction with peers by replying to their posts. Finally, popularity and expansiveness tend to indicate the existence of students who receive a significant number of replies to their posts or students who tend to reply more often to their peers' posts, respectively.

The existing research provides evidence that cyclic and transitive triples are the common characteristics of social media networks (Lusher et al., 2012). In directed networks, these two statistics are captured within the triangle term (i.e., a configuration of links that forms a triangle of nodes in a network) (Goodreau et al., 2009; Lusher et al., 2012). Nevertheless, models with triangle term are almost always degenerate (i.e. cannot be fitted). Therefore, geometrically weighted edgewise shared partner distribution (gwesp) was used instead (Goodreau et al., 2009). We also modeled Simmelian ties (Krackhardt, 1999) in order to examine whether the analyzed network(s) exhibit a formation of cliques of students that tend to interact with each other significantly more often than with the rest of their peers. Such a statistic could indicate that those students have primarily being focused on their specific field of interest and rarely interacting with other students.

### ***Network properties and learning outcomes***

Addressing our **fourth research question** assumed a two-step analytical procedure: i) extracting network structural properties, and ii) examining the association between learning-related metrics (i.e., discussion participation patterns and social positioning) and learning outcome. To examine **network structural properties**, we relied on the most commonly used SNA measures that capture various

aspects of network structural centrality – weighted degree, closeness, and betweenness centrality (Wasserman, 1994). Weighted degree centrality accounts for the weight of edges a node has in the network. Closeness centrality indicates the potential for having control over communication in a network, by measuring the distance of a given node to all other nodes in the network. Specifically, closeness centrality measures nodes' potential to connect easily with other nodes. Finally, betweenness centrality is also related to the potential for control over communication; however, betweenness instead shows which nodes might expect benefits due to having the role of brokers in the network (Wasserman, 1994).

Finally, we built two multiple regression models, one for each analyzed course. Each regression model included one dependent (i.e., final course grade) and five independent variables (degree, closeness, betweenness centrality, post count, and transition count). Both models indicated a satisfactory fit, having variance inflation factor (VIF) less than 2 for all the variables observed (Field, Miles, & Field, 2012). However, since both models indicated potential issues with heteroscedasticity, we report coefficients calculated using White's (1980) heteroscedasticity-corrected covariance matrices to make inference.

All the analyses were conducted using the R software language for statistical analysis (R Core Team, 2014).

## 4. Results & Discussion

### 4.1. Conversation Modeling – speech acts (RQ1)

Fitting block HMM (Paul, 2012; Ritter et al., 2010) resulted in six speech act categories in both courses analyzed (Table 2). However, we were not able to detect all the categories proposed in the Searle's (1976) speech acts categorization (*representatives*, *directives*, *commissives*, *expressives*, and *declarations*). Instead, we identified three subcategories of *Directive* speech acts (questions & answers, instruction, and elaboration), *Expressives*, *Representatives*, and a category of messages that could not be characterized as any act of speech, and thus was labeled *Other*. Table 3 shows descriptive statistics of students' and teachers' contribution to different categories of speech acts. On average, students' contribution across the categories of speech acts was higher and more evenly distributed in the FP course. Similar to the existing research findings (Gillani & Eynon, 2014; Qadir & Riloff, 2011), the highest number of messages belonged to directive speech acts. Specifically, in discussion forums of both courses included in the study, a majority of messages posted by students and teachers was categorized as *questions & answers*.

TABLE 2.  
SPEECH ACTS EXTRACTED FROM TWO DISCUSSION FORUMS UNDER THE STUDY, WITH THE LIST OF TOP WORDS AND  
CHARACTERISTIC FORUM MESSAGE

Speech act	Top words <i>Example</i>
<b>Delft Design Approach</b>	
Directives Q&A	<p>your , it we ? assignment in will ! peer not can video if that course</p> <p><i>Sorry, but now the assignment 6/7 deadline has moved to January 6th? If this is true it will be very welcome. Because I've been pretty ill and don't know if I can finish before deadline of the 16th december.![dealine changed for week 6&amp;7][1]</i>  <a href="http://edxuploads.s3.amazonaws.com/1418590078292102.png">http://edxuploads.s3.amazonaws.com/1418590078292102.png</a></p>
Directives Instruct.	<p>we your peer as assignment courses problem deadline platform // issue technical manage has https</p> <p><i>We postponed the deadline until Friday 21st 23.59 UTC. Please upload your results, so your peers can review it and you can learn from them. Good luck!</i></p>
Directives Elaborate	<p>in design , that are ? with or it process we as . not be</p> <p><i>Hi, I don't think you should completely rephrase your design challenge. What you could try is making sub-problems within your design challenge, and try to come up with ideas for those first. Afterwards you can try to combine them into more hollistic ideas and concepts. I hope this has answered your question!</i></p>
Expressiv.	<p>in design am , i'm my course . hello name learn with everyone hi an about</p> <p><i>Hi [name]!! I am [name], living in [city]. I have studied informatics, and I am also taking this course for the same reasons. Nice to meet you!!</i></p>
Represent.	<p>video // it my your ? link assignment http not com be upload was youtube</p> <p><i>The assignment template details were not legible but the video turned out well :).Thanks for sharing.</i></p>
Other	<p>// com https s3 edxuploads amazonaws jpg my design ! www http ? video youtube</p> <p><i>![assignment3][1][1]: <a href="http://edxuploads.s3.amazonaws.com/14173737885950747.jpg">http://edxuploads.s3.amazonaws.com/14173737885950747.jpg</a></i></p>
<b>Functional Programming</b>	
Directives Q&A	<p>the I to . that it you of and for course ! on was have</p> <p><i>Is there anyway we can get some faster mirrors for downloading the lecture videos? 30+ minutes for 720p and 4+ hours for 1080p is a really long time.</i></p>
Directives Instruct.	<p>a x type f , function the is of b t * y that string p parser</p> <p><i>Sheer nonsense. You can use "x y -&gt; x + y * y" with "Double"s, so that also breaks "a strict 'Int -&gt; Int -&gt; Int' requirement". None of the example functions have 'Int -&gt; Int -&gt; Int' as their most general type.</i></p>
Directives Elaborate	<p>of to . that the / I and a is in programming ; haskell functional</p> <p><i>Can anyone develop the relationship between the recursive approach and mathematical induction? Induction "goes forward" and covers and infinite sequence whereas problem 7 "moves backward" to cover all cases of a finite set. The use of the null set in sequences is also an indicator that there is a relationship. I would be interested in an infinite sequence developed through recursion to compare."</i></p>
Expressiv.	<p>the a I of action to that type function it is b f concurrent ' you</p> <p><i>Yes, I ran into at least one implementation of fork that typed check correctly but caused an infinite loop when implemented. I'm certain there are many others.</i></p>
Represent.	<p>, 1 x 2 3 xs a n the list 0 of 4 5 is integer</p> <p><i>You made a typo with that option. You wrote '[xs]' instead of just 'xs' in the end.</i></p>
Other	<p>/ . // 1 http org https haskell com www courses fp101x delftx 3t2014 0</p> <p><i>It's a bird! It's a plane! ![[1] [1]: <a href="http://bodil.org/more-than-functions/m/lambda-man.jpg">http://bodil.org/more-than-functions/m/lambda-man.jpg</a></i></p>

Our analysis revealed three broad categories of *directive* speech acts, in both courses analyzed (Table 2). *Directive* acts, as defined by Searle, represent a speaker’s attempt to “get the hearer to do something” (Searle, 1976, p. 11) – e.g., ask a question, invite, or advise. Studying the use of directives or prohibitions in the context of social learning, Ervin-Tripp (1979) showed a wide diversity of structural variations that adults rely on in conveying directive speech acts. With respect to the general intention of the posts identified in the directives group and the nature of interactions (e.g., student-student, student-teacher), we further categorized directive speech acts as: *questions & answers*, *instructions*, and *elaborations*. These specific variations of directives we detected could be also found in previous related research, where Merceron (2014), Kim et al. (2010), and Arguello and Shaffer (2015), among others, relied on particular dialog acts, such as answers, questions or issues.

TABLE 3  
DESCRIPTIVE STATISTICS OF THE FORUM MESSAGES POSTED IN DIFFERENT SPEECH ACT CATEGORIES, SHOWING TOTAL, AVERAGE NUMBER AND STANDARD DEVIATION (STUDENTS AND TEACHERS), AS WELL AS NUMBER AND PERCENTAGE OF MESSAGES CONTRIBUTED BY TEACHING STAFF

Course	Speech act	Total # Msg.	Average # (SD) per student	Teacher contr. (%)
DDA	Directives Q&A	735	4.02 (12.44)	264 (36%)
	Directives	54	2.16 (2.39)	19 (35%)
	Instructions			
	Directives Elaborate	362	2.18 (2.31)	37 (10%)
	Expressives	508	1.21 (0.78)	12 (2%)
	Representatives	379	2.56 (4.30)	50 (13%)
	Other	460	1.66 (1.89)	2 (0.4%)
FP	Directives Q&A	3243	4.59 (19.87)	611 (19%)
	Directives	752	3.20 (8.84)	108 (14%)
	Instructions			
	Directives Elaborate	1041	3.90 (13.88)	153 (15%)
	Expressives	1361	3.22 (7.42)	149 (11%)
	Representatives	1010	2.77 (6.14)	102 (10%)
	Other	786	3.49 (12.16)	207 (26%)

It is interesting to note that in both courses we identified *Directives (questions & answers)* speech acts to be primarily focused on student-teacher interaction. *Directives (instructions)* speech acts were characterized by posts aimed at providing certain instructions – such as course related information (Table 2). This category might be related to directive statements or hints, as defined by Ervin-Tripp (1979). *Directives (elaboration)* acts were mainly oriented towards the deeper knowledge construction and (primarily student-student) interactions that aimed at more comprehensive elaboration of the topic under discussion.

*Expressives* as a particular type of social interactions, was mostly characterized by messages that expressed certain psychological states (such as appreciation for provided answer) (Searle, 1976). However, in an extended meaning and similar to the study by Qadir and Riloff (2011), in our study, this category also included messages that reflected specific personal experience (Table 2). This suggests that in the context of online discussions, the category of *Expressive* speech acts captures social interaction that can be qualified as a *socio-emotional conversation*, as defined by Poquet and Dawson (2016), or *interpersonal* and *open communication* as defined by Garrison and Akyol (2013). More formally defined, and in line with Qadir and Riloff (2011), we tend to observe *Expressives* in discussion forums as a speech act category that conveys appreciation, complimenting, expressing agreement, and conventional expression of emotions or student personal details (Garrison & Akyol, 2013).

We were also able to observe the *Representative* speech act – an illocutionary point that depicts a student’s (originally a speaker’s) “belief of something that can be evaluated as true or false” (Qadir & Riloff, 2011, p. 750). Considering *Representative* acts from a broader perspective (similar to Qadir & Riloff, 2011), we recognized as *Representative* those messages that pointed to certain conclusions (or evaluations) that indicated students’ understanding of something being the case. For example, providing a solution to a previously posted problem (Table 2).

Finally, both courses were characterized with a particular group of messages that did not have indicators of an intended social activity. Given that there was no sincerity condition in the form of those messages, that is, they could not be categorized as assertive, commissive, directive, or expressive point (Bazerman, 2004; Searle, 1976), we were tempted to label this category as declarative speech acts. However, those messages did not imply any kind of “alteration in the status or condition” (Searle, 1976, p. 14), or had the strength of declarations as originally defined. Their primary purpose was to submit an assignment or point to a specific resource (Table 2), without an intent to carry out a specific act (Bazerman, 2004). Therefore, they were coded as *Other*.

*Declaration* speech acts were not identified in the examined discussion forums. This finding is in line with Qadir and Riloff (2011), for example, who also did not observe this category in discussion forum posts obtained from a professional learning network. Given the nature of interaction in digital educational settings, it is rather unlikely to expect statements like the ones declaring a war or firing someone (Qadir & Riloff, 2011; Searle, 1976).

Likewise, we were not able to identify *commissives* – *illocutionary point that occurs when speaker commits to a future action* - as a distinct category. One of the possible explanations might stem from the unit of analysis used in the study. Specifically, we relied on a message as a basic level of communication between course participants (i.e., students and teachers or students and their peers). Thus, it does not mean that there were no utterances (e.g., sentences), that could be classified as

commissives (Section 2.1). As a matter of fact, our qualitative examination of messages did indeed reveal sentences where students (or teachers) obliged to take some further actions. For example, the following sentence:

“...*What I'll do, I will make a screenshot of the text written and if this text is indeed yours [NAME], than I could assess it after all!...*”

could be classified as a *Commissive* speech act. However, this utterance represents a part of a longer message that was ultimately categorized as *Directives (questions & answers)*, which indeed depicts a role this message had in the social interaction.

#### 4.2. Conversation Modeling – dynamics (RQ2)

The second research question focuses on further investigation of students' and teachers' conversation patterns that reflect a coherence of the shared discourse as well as a sequence of speech acts used in a discussion.

The overall contribution (in terms of the number of messages posted to a discussion forum) of the teaching staff (including course instructors and teaching assistants) in both courses was rather similar: 17% of the total number of messages in the DDA course, and 19% in the FP course. However, Table 3 shows rather diverse patterns — with respect to contribution to different categories of speech acts – of posts created by the teaching staff within the two courses analyzed. It seems that the teaching staff in the DDA course were primarily focused on providing support in answering questions and administering instructions related to the course organization, with more than 35% of messages contributed to *Directives instruction* and *Q&A* speech act categories (Table 3). This observation is in line with Arguello and Shaffer's (2015) finding that teachers tend to intervene by responding to those messages that introduce a certain problem. On the other hand, participation of the teaching staff in the FP course seemed to have been more balanced, in terms of similar amount and percentage of posts contributed to each of the speech act categories (Table 3).

Student conversation dynamics in the two analyzed courses also differed as evident from the discussion forum participation patterns shown in Figure 1 and Figure 2. We modeled student conversation from two aspects. First, we observed the relative percentage of the number of students who created discussion posts in different categories of speech acts (Figure 1), similar to the work by Merceron (2014). Additionally, we also examined to what extent students tend to post across different categories of speech acts or whether they rather clustered their contribution within a single category. (Figure 2) (Gillani & Eynon, 2014; Poquet & Dawson, 2016).

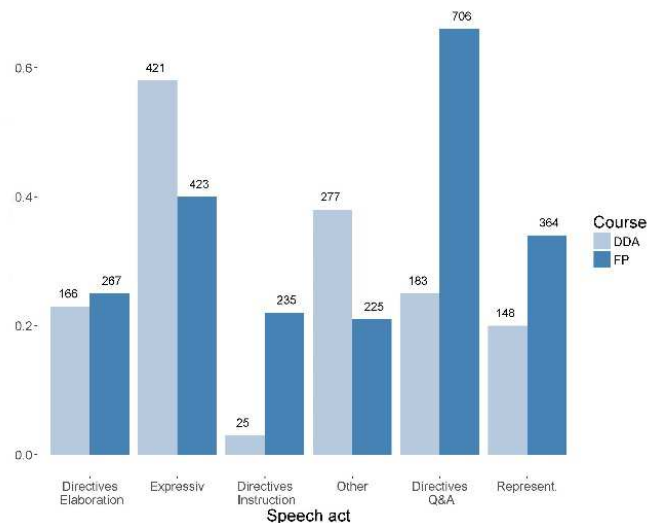


Figure 1. Percentage of students who contributed to course discussion by posting messages in each of the speech act categories, with labels showing exact numbers of students.

The highest percentage of students who posted to the DDA discussion forum focused on creating posts categorized as *Expressive* speech acts (Figure 2). That is, it seems that a majority of students focused on *socio-emotional non-task* conversation that is about social, rather than cognitive, aspects of learning in MOOCs, such as introductions (Poquet & Dawson, 2016; Qadir & Riloff, 2011). For example, the following message includes indicators of interpersonal and open communication, as defined by Garrison and Akyol (2013):

*“Hi, My name is [NAME], I’m an industrial designer from [CITY, STATE]; I enrolled this course because I’m really into design and I strongly believe that within design my country can progress and improve the industry and economy. I’m [YEAR] years old, and I have been working in fashion industry in [STATE], I have only my Bachelor degree and right now I’m looking for a master overseas in order to complement my education; what would you suggest me? Thanks!!!! Regards [NAME]”.*

The DDA course also had a high percentage of students with posts in the *Other* category. This category primarily included those messages where students simply submit an assignment or share a resource. Such messages usually contain just a URL, without further discussion. Given that there were five assignments in the DDA course, an average of 1.66 posts per student (Table 3) could suggest a very low engagement with the assessment. Figure 1 further shows a noticeably high number of students whose posts belong to the *Other* category only, whereas Figure 2 further shows a substantially high overlap between students who posted to both *Other* and *Expressives* categories. As previously elaborated, *Expressive*



speech acts, as understood here, were primarily social in the nature, without necessary intent to engage into deeper learning processes.

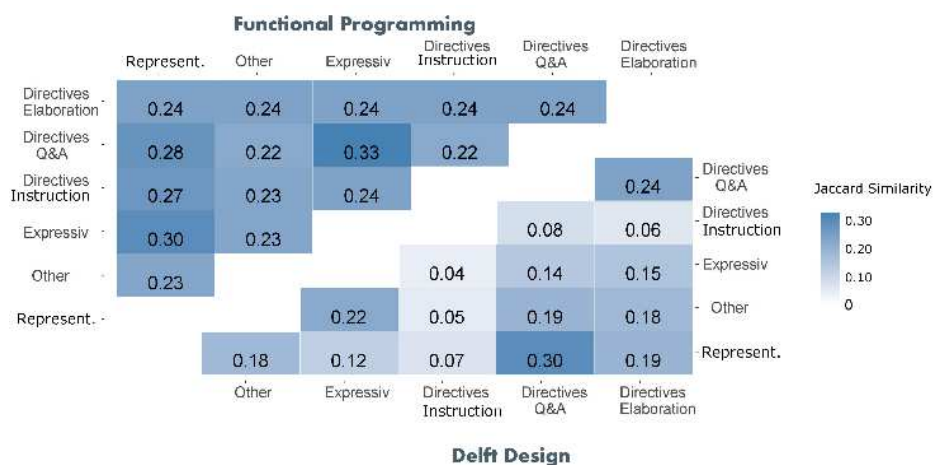


Figure 2. Similarity of students based on their posting patterns in pairs of different speech act categories; color-codes and numbers show the value of Jaccard similarity index, the metric used for computing the similarity

Student participation patterns in the FP course, on the other hand, seem to be aligned with the contemporary research on MOOC discussion forums (Arguello & Shaffer, 2015; Gillani & Eynon, 2014; Merceron, 2014). Specifically, Figure 1 shows that the highest number of students who were engaged with the discussion forum tended to ask for help or provide assistance to their peers (Arguello & Shaffer, 2015; Poquet & Dawson, 2016). Additionally, a noticeable number of students focused on social interactions (*Expressives*) and contributions that take the general form of *Representative* speech acts. The student participation matrix – that indicated how similar students were in terms of their posting patterns in various pairs of speech act categories (Figure 2) – suggests that there was a considerable similarity between students in terms of their posting patterns in *Directives Q&A* and other categories of speech acts. Moreover, the matrix indicates that while the students' engagement in the discussion forum of the FP course was primarily focused on help seeking, it was lacking elaboration. This finding suggests the lack of interest in continuing collaboration with peers (Arguello & Shaffer, 2015; Merceron, 2014).

Finally, we also examined what speech acts students commonly used to start a discussion and how these speech acts changed in subsequent interaction. It is interesting to note that in both courses, a majority of threads started as *Expressives* (40% of threads in DDA and 35% in FP). Given our understanding of *Expressive* speech acts in discussion forums as means to establish a social connection, this finding aligns with the existing literature in digital educational settings (Garrison & Akyol, 2013; Poquet & Dawson, 2016). For example, the original model by Garrison and Akyol (2013) posits that this form of communication should indicate the inception of community formation

in online settings. Given the wide diversity of learners in MOOCs and challenges related to fostering social interactions and development of learning communities at scale (Gillani & Eynon, 2014), it seems reasonable to expect that a considerable amount of conversation begins with *Expressive* speech acts.

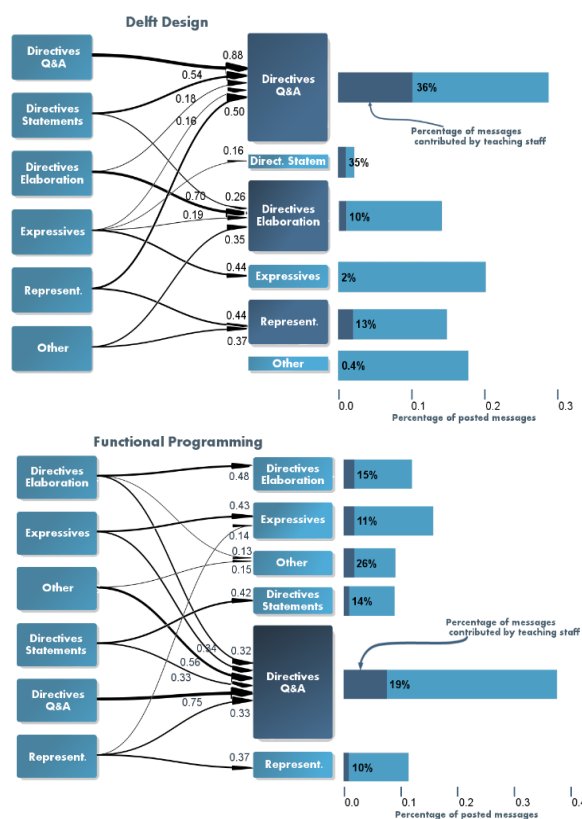


Figure 3. The likelihood of transitions between different speech act categories where a larger arrow width represents higher likelihood (exact probabilities are represented with numerical values). The right part of the figure represents percentage of messages posted within each of the speech act categories, with highlighted values showing the contribution made by the teaching staff.

Table 3 and Figure 3 suggest that a majority of discussion threads tended to converge towards the category of posts that includes higher student-teacher interaction, with the primary intent to communicate problems students encountered and provide solutions to those (i.e., Directives Q&A). Merceron (2014) and Gillani and Eynon (2014) also found questions and answers being the most prominent categories that characterize student interaction in MOOCs. However, certain differences in transition patterns (i.e., thread coherence) were also identified in the two courses (Figure 3). Specifically, while both courses were characterized with high probabilities of either transitioning to the *Directive (questions & answers)* category, or remaining within the original category, there were certain differences with respect to the *Directive (elaboration)* and *Representative* speech acts. The

difference is present in the tendency for the conversations in the DDA course to converge towards those speech acts that might suggest higher presence of knowledge building processes – i.e., *Representative* and *Directive (elaboration)* speech acts (Levinson, 2017). This pattern was not present in the FP course. Conversations (i.e., threads) in the FP course tended to be more homogenous – starting and completing with questions and answers or remaining within the same speech act category. Conversation dynamics, as depicted in Figure 3, suggests that threads in the DDA course were more heterogeneous, allowing more often (compared to the FP course) for conversation to converge towards the group of messages characterized as *elaborative Directive* or *Representative* speech acts. An example of an *elaborative* post is shown below:

*“This is a very interesting and potentially wide ranging question that you've raised. I don't think that competition necessarily hinders creativity. But sometimes people may act more in their own self interest, perhaps out of a desire to "win" some fortune or status. I think that there is plenty of competitiveness (socially and economically) in Scandinavia and Northern Europe; probably just as much as in the other countries you mentioned. If you haven't watched any movies or read any books by people from those cultures, then I suggest you try some. (I enjoyed, [Borgen][1] , and [The Killing][2]). These show that competitive behaviour is not beyond the realm of their imagination. A further survey of the daily news from these places will probably confirm less spectacular examples. Although I don't agree with limiting access to food/water, healthcare or education, there are theories that claim competition may actually help people to achieve goals faster and to improve their performance. Maybe even to innovate (I'm thinking of the fabled, Space Race). Having said all that. I'd be interested to hear from the design researchers and economists on this one. [1]: [URL] [2]: [URL]”.*

That is, instead of directly providing a resolution to a problem, this post introduces different views and suggests consideration of additional aspects of the initial investigation.

Summing up the results presented so far, using methods of discourse analysis, we were able to reveal six interpretable “groups” of messages characterized by a specific illocutionary point (i.e., having specific meaning in social interaction). We have also observed and discussed certain differences in communication patterns in the two courses under study. Given that social actions are often accomplished through language (Bazerman, 2004), we aimed at further investigating to what extent the observed patterns reflect the social dynamics that drive network formation in the examined courses.

### 4.3. Network Characteristics (RQ3)

Statistical network analysis allowed us to complement our findings from the discourse analysis, and thus obtain more comprehensive insight into the learning process. Table 4 presents the two best fitting exponential random graph models, as indicated by the lowest AICc values. Goodness-of-fit statistics provided a satisfactory fit for the data analyzed.

It is interesting to note that for both networks, indicators of student conversational patterns yielded a significant positive effect on tie formation. That is, the number of posts and the diversity of speech acts employed (i.e., transition count) in forum discussions were positively associated with the number of ties students created in social interactions. A considerably higher estimate for the transition count might further suggest that a simple participation (expressed through the post count) was not sufficient. What seems to be more important is the use of different acts of speech when communicating with peers and/or teachers.

Further, both networks indicate a significant effect of the homophily based on the final course outcome (passed or failed the course in this case). This finding is in line with the existing research finding that homophily based on the achievement level represents one of the defining characteristics of the networks emerging from MOOC discussion forums and online learning settings in general (Joksimović et al., 2016; Kellogg et al., 2014; Vaquero & Cebrian, 2013). The effect of reciprocity (i.e., mutual ties) was positive and significant in both networks, suggesting that the *two-way interaction* among students or between students and teachers, occurred more frequently than it would be expected by chance (Goodreau et al., 2009). This tendency towards forming mutual ties between peers (i.e., continued interaction) has been recognized as one of the defining characteristics of interactions in online social networks (Joksimović et al., 2016; Kellogg et al., 2014; Lusher et al., 2012)(Lusher et al., Kellogg et al., Joksimovic et al.). It contributes to the creation of a comfortable learning environment that supports efficient knowledge sharing (Lusher et al., 2012). On the other hand, the results of discourse analysis (Section 4.2) suggest that students in the FP course were mainly focused on help seeking (and perhaps answering), i.e., the *Directives Q&A* category of speech acts. This kind of discourse seems to contribute more to the development of focused discussions in small groups and high “modularity in communicative tendencies” (Gillani & Eynon, 2014, p. 22), as also evident based on the negative effect of popularity spread and expansiveness (Table 4) (Lusher et al., 2012).

It is further revealing that the network that emerged from the DDA discussion forum was characterized by the significant effect of transitivity (Goodreau et al., 2009; Simmel, 1950). The effect itself suggests a tendency for the forum participants to cluster together, suggesting traces of collaborative and/or cooperative work. However, our further results show that connections within such

clusters in the DDA course did not evolve to Simmelian (i.e., super-strong) ties (Krackhardt, 1999), as it was the case in the FP course (Table 4). Being embedded within relatively small, highly cohesive groups (or cliques), Simmelian ties point to the existence of interactions that are qualitatively and quantitatively different from other connections within a network. The existence of Simmelian ties might indicate a tendency towards high fragmentation among forum participants and interactions within small groups of students (Gillani & Eynon, 2014). The nature of discourse in the FP course further suggests that those super-strong ties could have primarily emerged from students' behavior that was characterized by seeking help, and providing solutions to help the inquires of others. It is, however, unclear, to what extent teachers' activity influenced the formation of super-strong ties in the FP course. A possible reason for this could be that a more diverse contribution of the teaching staff in the FP course as compared to that of the teaching staff in the DDA course could have been one of the factors that framed social interactions in this particular way.

TABLE 4  
SUMMARY OF ERG MODELS ESTIMATES FOR DDA AND FP COURSE

	DDA		FP	
	Estimate	SE	Estimate	SE
Baseline (Edges)	-7.459***	0.126	-7.817***	0.075
<b>Selective Mixing</b>				
Achiev. (fail)	-0.354***	0.099		
Achiev. (pass)	0.646***	0.103		
Achievement	-		0.403***	0.035
<b>Indicators of Conversational Patterns</b>				
Post count	0.004***	0.001	0.002***	0.001
Transition count	0.467***	0.024	0.434***	< 0.001
<b>Structural Mechanisms</b>				
Reciprocity	2.271***	0.251	3.608***	0.082
Simmelian ties	-		0.118***	0.047
Transitivity	0.455***	0.092	-	
Popularity	-1.362***	0.146	-0.561***	0.093
Expansiveness	-		-0.824***	0.093

Note: \*  $p < .05$ . \*\*  $p < .01$ . \*\*\*  $p < .001$ .

Aiming to deepen our understanding of the formation of super-strong ties in the FP course, we refer to the notion of *common ground*, that is, the presence of shared information in any communication act between two peers, either online or face-to-face (Poesio & Traum, 1997; Xin & Feenberg, 2006). The common ground represents artefacts generated in the communication process that peers employ in “articulating their positions and developing solutions” (Xin & Feenberg, 2006, p. 15). According to Xin and Feenberg's (2006) framework, a successful communication is characterized by constantly growing the common ground that is reflected through a variety of speech acts employed

in the interaction. Figure 2 shows a considerably higher similarity of students' posting patterns across different pairs of speech acts in the FP course compared to those of the students in the DDA course. Furthermore, Figure 3 shows that most of the FP discussion threads converged towards questions and answers acts, and it is this category that is necessary for reaching the common ground among the communication participants (Traum & Allen, 1994). Therefore, it seems that the amount of information shared, depicted through different speech act categories employed, is a determining factor that leads towards establishing qualitatively stronger ties between course participants.

#### 4.4. Achievement, Discourse, and Networks (RQ4)

Our fourth research question was aimed at examining to what extent the characteristics of social interactions in a discussion forum provide basis for interpreting the association between learning-related social constructs (namely engagement with peers and social centrality in a discussion forum) and learning outcome (operationalized through the final course grade). Specifically, following the conclusions from Joksimović et al. (2016) study, we expected a significant association between the network centrality measures and course outcome, in the case of the DDA course. However, that should not be the case in the FP course, given the significant tendency towards the formation of Simmelian ties in that course. As argued by Krackhardt (1999), being embedded into super-strong ties, does not necessarily imply benefits and could potentially introduce constraints Krackhardt (1999). Additionally, we also observed the association between forum participation patterns, operationalized through the number of posted messages and number of transitions between different speech act categories with the final course grade (Table 5).

TABLE 5  
RESULTS OF THE REGRESSION ANALYSIS OF THE ASSOCIATION BETWEEN STUDENT POSTING BEHAVIOR, SOCIAL CENTRALITY AND FINAL COURSE GRADE

Variable	DDA				FP			
	Est.	$\beta$	SE	t	Est.	$\beta$	SE	t
Post count	<b>6.62***</b>	<b>0.49</b>	<b>1.24</b>	<b>5.35</b>	2.67	0.06	3.12	0.86
Trans. Count	0.15	0.10	0.12	1.29	<b>0.39***</b>	<b>0.28</b>	<b>0.08</b>	<b>5.17</b>
W. Degree	<b>-2.03*</b>	<b>-0.18</b>	<b>0.93</b>	<b>-2.17</b>	0.84	0.04	1.45	0.58
Between.	-0.81	-0.03	1.80	-0.45	-5.99	-0.05	5.56	-1.08
Closeness	<b>0.10**</b>	<b>0.17</b>	<b>0.03</b>	<b>3.14</b>	0.04	0.04	0.03	1.12

In the DDA course, which *was not* characterized with the tendency to form super-strong ties between the course participants, we *were able* to observe significant effect of the number of posted messages ( $\chi^2(1) = 5.35$ ,  $p < .001$ ), weighted degree centrality ( $\chi^2(1) = -2.17$ ,  $p = .015$ ), and closeness centrality ( $\chi^2(1) = 3.14$ ,  $p < .001$ ). The model explained 26% of variance in students' final course grade. Thus, as expected (Joksimović et al., 2016), there is a significant association between the social

positioning and final course outcome. However, whereas the direction of fit for the student activity in discussion forum is positive, the weighted degree and students' potential for control of communication (i.e., closeness centrality) were negatively associated with the outcome\*. These results might be explained with the forum participation patterns. Specifically, even though a majority of students who contributed to the DDA discussion forum posted messages that were characterized as either *Expressives* or *Other*, the average number of messages contributed to these two speech act categories was rather low (Table 3). These factors suggest rather shallow communication in the DDA course, that could explain the negative association between centrality measures and final course grade.

In the FP course, we were able to observe a significant and positive effect only in the case of the transition count (i.e., how many times students transitioned from one speech act to another in their forum contributions):  $\chi^2(1) = 5.17$ ,  $p < .001$ . Given Krackhardt's (1999) interpretation of the super-strong ties, and results of our previous study (Joksimović et al., 2016), the lack of the association with centrality measures was rather expected. The significant association between the final course grade and the number of transitions between different speech acts could be explained with a more diverse discourse for those students who had a higher number of transitions. That is, the higher number of transitions between different categories of speech acts could indicate a communication between students with a higher amount of shared information (i.e., common ground, as explained in Section 4.3). The model, however, explained a comparably lower amount of variance (12%) than in the case of the DDA course.

## 5. Conclusion and Implications

Discourse and social network analyses have a long tradition in educational research in general, and learning analytics in particular. Nevertheless, they have been commonly applied as separate analytical approaches that allow for obtaining insight into the learning process from two different perspectives, rather than as a set of complementary approaches. This study suggests that combining discourse and social network analyses could potentially provide more comprehensive insights into the process of learning in networks emerging from interactions in digitally connected, computer mediated settings.

In this study, we primarily grounded the theoretical framework in the speech acts theory (Bazerman, 2004; Searle, 1976), as means for investigating intended meaning (i.e., speech act) of the communication in MOOC discussion forums. Relying on unsupervised methods for discourse analysis, namely block HMM (Paul, 2012), we were able to identify, in an automated way, common

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\* As smaller values of closeness centrality are indicative of higher control of communication, the positive values of the estimate in the regression model are indicative of the negative association.

groups of speech acts emerging from discussion forums of the two MOOCs analyzed. Further, different conversational patterns evident in the students' contributions to the studied discussion forums revealed rather distinct social dynamics that framed emerging social networks. For instance, we were able to show that a discourse characterized by rather homogenous threads (in terms of speech acts), primarily focused on Q&A sessions, and with a substantial common ground (i.e. shared information), is associated with evolution of super-strong ties.

Complementing discourse analysis with the methods of statistical network analysis, we were further able to interpret an association that social centrality and forum participation have with the final course outcome. Specifically, for predicting course grade in a course that is characterized with a close interaction between discussion forum participants (as in the analyzed FP course), it seems that a simple participation and social centrality are not features of great importance. Such findings are in accordance with the results from the previous work (Joksimović et al., 2016), which provided an insight into the discourse properties that could be associated with different network configurations.

Our findings suggest several important implications for further research and practice. Whereas the algorithm used in this study (i.e., block HMM – Paul, 2012) was previously evaluated using the discussion data from other online communication platforms (i.e., Twitter and CNET), this study showed that the same approach could be successfully applied in more structured educational settings – i.e., to analyze MOOC discussion forums. Further, even though speech acts analysis at the message level provides useful insights into conversational dynamics, as confirmed in this and previous studies (Arguello & Shaffer, 2015; Merceron, 2014), further research should explore approaches that use individual utterances as a unit of analysis. Such an approach would provide more fine grained insights into emerging conversational patterns.

One of the notable differences with respect to the communication patterns observed in the two examined discussion forums was related to the patterns of teachers' participation. Although learning at scale in general, and MOOCs in particular, is student-centered and heavily depends on students' motivation to engage and regulate their learning (Jones, 2015), our study suggests that the formation of small, highly cohesive groups, (i.e. groups characterized by super-strong ties) might depend on the presence and role of the teacher. This could be further related to the instructional design that, in the case of the analyzed courses, did not assume grading of students' discussion contributions (Gašević, Adescope, Joksimović, & Kovanović, 2015). Nevertheless, it seems rather important to further explore how and to what extent teachers' participation could affect students' participation in discussions.

From the practical perspective, the approach presented here, could provide teachers with valuable information about student participation in a discussion forum. For example, relying on the proposed approach, teachers could obtain a comprehensive (automated) summary of discussion threads students



are involved with, which could further allow for a more advanced feedback provision than present tools offer (Kovanović et al., 2017). Moreover, by understanding factors that influence interactions in discussion forums, teachers would be better able to validate certain indicators of learning and make informed decisions about required interventions.

Several limitations of our study need to be acknowledged. First, the study observed students' interactions within discussion forums of two courses with different subject domains. Still, further analysis should also consider courses from other disciplines. Further, given that the assessment is recognized as one of the most powerful ways to influence student motivation and achievement (Cauley & McMillan, 2010), it seems rather important to replicate the method presented in this study with courses that include graded discussion. Finally, this study did not account for students' motivation to participate in a course, their level of education, or previous experience with online courses (and MOOCs in particular). Although a majority of students fail to submit survey data (N. M. Hicks et al., 2016), this line of research could potentially provide additional insights into the factors that shape social interactions in MOOCs.

### **Acknowledgement**

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## 5.4 Summary

Learner generated discourse is considered the cornerstone of various educational theories and frameworks (Vygotsky, 1978; Bandura, 1977; Siemens, 2005) and one of the richest sources of information (in addition to self-reports) about cognitive, metacognitive, affective and motivational aspects of engagement in learning and understanding of learning material (Azevedo, 2015; Graesser, 2015; Goodyear, 2004; Jones, 2008; Stahl, 2004). Studying educational discourse is essential in revealing meanings shared in the classroom context and understanding factors that promote and contribute learning (Coll and Edwards, 1997). With the most recent socio-technical innovations and emergence of digital learning infrastructures, studying educational discourse, however, brought a whole set of new opportunities and challenges in extrapolating meaning from shared artefacts in face-to-face and online educational environments (Dowell *et al.*, 2017).

The proposed conceptual analytics-based model introduced in the first two chapters of this thesis argues for examining learner generated discourse as one of the necessary components to understand learning networks emerging from learners' interactions in learning with MOOCs. Primarily analyzing cognitive and affective aspects of learner engagement expressed through language and discourse used in social interactions, I observe factors that contribute learning. It should be noted here that aspects of cognitive and affective engagement have been limited to the analysis that rely on theoretically grounded linguistic proxies that are being associated with cognitive, affective, or social processes (Dowell *et al.*, 2016), exploration of topics being discussed, and analysis of speech acts employed in communication (Levinson, 2017; Carretero *et al.*, 2015; Baker *et al.*, 2013), as presented in Section 4.3, Section 5.2, and Section 5.3. Discourse, however, is not a static phenomenon (Goodyear, 2002; Jones and Steeples, 2002; Jones, 2015). Discourse evolves through the process of learning and is shaped through learners' engagement with their peers, teachers, and learning materials (Jones, 2008). Therefore, the proposed model does not observe discourse in isolation, but rather as a construct that is tightly connected to the emerging structures of social interactions and dynamics of learning with MOOCs.

The first study in this chapter (Section 5.2) investigate aspects of knowledge sharing within a learning network in a distributed educational environments (i.e., using social media, such as Twitter, blog and Facebook). In so doing, I proposed a novel approach to topic modeling that integrates automated keyword extraction, graph theory, and in-depth qualitative analysis. This methodological contribution demonstrated the importance of learner interests when representing socially constructed knowledge in learning networks. Specifically, the study represents a validation of certain ideas of connectivism - e.g., learners were primarily focused on the course topics they were interested in, regardless of the topics suggested by the course facilitators, while the technology had a significant impact on how learners discussed those topics (Siemens, 2008, 2005). On the other hand, from the practical perspective, building a trustworthy community in diverse and large networks, as those emerging from cMOOCs, is recognized as one of the important challenges (Mak *et al.*, 2010). Being able to reveal topics discussed



in different media and among emerging social groups might help learners to “bridge the social gap” and more easily reach groups of learners with similar interests.

The second study (Section 5.3) goes beyond research introduced in this and the previous chapter, providing the most comprehensive insights, which this thesis offers, into understanding of complex associations between structure, discourse, and dynamics of learning networks. Combining methods of discourse and social network analysis into a single analytics-based approach, the study provides basis for moving beyond previously introduced attempts to combine these two complementary perspectives (De Laat, 2005; De Laat *et al.*, 2007), allowing for exploration of inferential statistical links between discourse and social structures. The proposed approach also provides insight into the sequences of actions employed in learners’ interactions as one of the essential means for understanding the process of knowledge construction (Stahl, 2004; Molenaar and Chiu, 2015). Thus, in addition to replicating results from the study introduced in Section 4.4 and showing how certain social structures (i.e., those characterized with super-strong ties) provide a context for the analysis of the association between learner engagement and outcome, this study also provides potential explanations about the factors that contribute to the development of such structures.

Through the analysis of discussion forum data from two MOOCs (Section 5.3), I was able to detect six categories of speech acts, categorized following Searle’s (1976) speech acts classification into *directives*, including three subcategories – *questions and answers*, *instruction*, and *elaboration* – *expressives*, *representatives*, and a category of messages that could not be characterized as any act of speech, and thus was labeled as *other*. In addition to understanding the role learners contribution played in collaborative knowledge creation, the analysis of learners’ and teachers’ conversation patterns allowed for examining a coherence of the shared discourse as well as a sequence of speech acts used in a discussion. The results suggest different communication patterns in the two MOOCs, primarily reflected in a discrepancy of transitions between the six categories of speech acts and the level of shared understanding between the course participants, as reflected in variability in discourse coherence in two datasets.

Different conversational patterns evident in learners contributions to discussion forums, further revealed distinct social dynamics that framed emerging social networks. For instance, we were able to show that discourse characterized by rather homogenous threads, primarily focused on Q&A sessions and with a substantial common ground (i.e., shared information), was associated with the formation of super-strong ties among the learners of one of the two MOOCs. On the other hand, although learners tended to engage in a more elaborative discourse, such interactions do not necessarily lead towards establishing stronger ties with their peers. Such discourse could rather indicate a lack of shared common ground and suggest a necessity to provide means for deeper learners’ engagement with the learning process in social interactions. Nevertheless, the observed differences in communication patterns and discrepancy in reflected social dynamical processes that drive network formation, yielded compelling implications for understanding the association between learner engagement and outcome of learning

in networked settings. Specifically, the findings of the study introduced in [Section 5.3](#) are in accordance with the work presented in [Section 4.4](#), arguing for the importance of considering contextual factors, such as the characteristics of emerging social structures obtained through statistical network analysis, in predicting learning outcomes based on learners' behavioral engagement, in case of this particular study.

Observing *discourse* generated in learning networks and temporal *dynamics* of discourse evolution in the process of knowledge building and sharing, the two studies that comprise the core of the present chapter illustrate a specific application of the conceptual model introduced in [Chapter 2](#). In examining relationship between the discourse and dynamics, the two studies explored the knowledge building activities that emerge in learning networks, *contextualized* within two different settings ([Section 5.2](#) and [Section 5.3](#)). However, [Section 5.3](#) goes beyond the previous research introduced in the present thesis providing insights into the relationships between the three main constructs that describe learning networks - i.e., discourse, structure, and dynamics ([Chapter 2](#)). In so doing, the study introduced in [Section 5.3](#) explores to what extent discourse and discourse dynamics helps explaining structure of learning networks emerging from learning with MOOCs.

# CHAPTER 6

## Summary

## 6.1 Discussion and Contributions

The thesis contributes to the development of learning analytics-based research in studying learning networks that emerge from the context of learning with MOOCs. In so doing, the thesis develops a conceptual analytics-based model that provides means for understanding learning networks from individual – i.e., *ego-centered* (Goodyear and Carvalho, 2014b) – and network levels. The proposed model provides a theory-driven conceptualization of the main constructs, along with their mutual relationships, necessary for studying learning networks. The thesis also offers an operationalization of the constructs identified in the model with the aim at providing learning analytics-methods for the implementation of assessment for learning. Finally, throughout the empirical work presented in the second part of the thesis (Chapter 4 and Chapter 5), the thesis provided an evaluation of the proposed model and introduced novel learning analytics methods that provide novel perspectives for understanding learning networks.

In this chapter, I briefly summarize the main findings and contributions of the work presented in the thesis. I structured the discussion around the research goals and questions introduced in Section 1.2, thus reflecting on some of the main contributions and implications for research and practice. Next, I revisit main methodological contributions of the presented research and discuss their implications. Finally, I outline some of the promising venues for future research.

### 6.1.1 Networked learning analytics: Development of the conceptual analytics-based model (RQ1)

The development of the conceptual analytics-based model for studying learning networks based on the principles of the ECD framework (Mislevy *et al.*, 2003) provides a theoretical and methodological grounding of the proposed approach in a broader literature of educational assessment. Specifically, relying on the concepts of student, evidence, and task models, allows for a straightforward implementation of assessment for learning in the context of learning in networked settings. As such, the proposed conceptual model (Chapter 2) defines key dimensions that should be observed in order to understand learning networks (i.e., discourse, structure, and dynamics). The conceptualization of the proposed model was driven by the existing network learning research (Goodyear, 2004; Goodyear and Carvalho, 2014b) and main principles of socio-cognitive theory (Bandura, 1977, 1986). Moreover, Chapter 3 provides detailed, theory-driven and analytics-based operationalization of the focal constructs introduced in the conceptual model (as operationalized within the second goal of the present thesis). Finally, across the five studies (Chapter 4 and Chapter 5) I proposed series of novel learning analytics approaches and methods that were utilized in order to provide an empirical validations of the proposed conceptual model. Therefore, the analytics-based model, introduced in the present thesis, provides a conceptual framework for designing, implementing, and customizing assessment for learning and understanding learning networks emerging from learning with MOOCs.

As outlined in Chapter 2, the three central elements that should be observed in order to obtain

a comprehensive portrait of learning networks emerging from learning with MOOCs are *structure* of interactions in a given contexts (Illich, 1971; Castells, 2004; Steeples and Jones, 2002; Goodyear, 2002; Fox, 2002), *discourse* produced as a result of those interactions (Goodyear, 2002; Jones, 2008; Ohlsson, 1996; Gee and Green, 1998), and *dynamics* of learning processes (Halatchliyski et al., 2014). My dissertation further showed that the three elements should be observed as interdependent constructs, in order to examine how i) social interaction factors shape discourse properties (and vice versa) and ii) how temporal dynamics frame network structural properties or influence development of discourse (Chapter 4 and Chapter 5).

Model conceptualization introduced in Chapter 2, and particularly study introduced in Section 2.2, also argues for the importance of understanding learning networks from the individual level. Building further on the research in social and learning sciences, the proposed model for studying learning networks relies on premises of social cognitive theory and Bandura's work (Bandura, 1977, 1986), accounting for *contextual*, *behavioral*, and *personal characteristics*, as part of the ego-centered (i.e., individual) perspectives (Goodyear and Carvalho, 2014a). These factors further contribute to understanding learning in learning networks by (i) comprehensively describing learning environments, learning contexts, and learners' personal characteristics, and (ii) enabling for a holistic interpretation of the model constructs and their relationships.

### 6.1.2 Operationalizing assessment for learning in networked settings (RQ2)

The second goal of the thesis was framed around the operationalization of the constructs defined within the proposed conceptual analytics-based model. In the context of the ECD framework, the second goal of the thesis was aimed towards a detailed specification of the evidence model in order to provide operationalizations of the focal constructs introduced in the student model. Such operationalizations should provide means for measuring dimensions of learning networks at the network level (i.e., discourse, structure, and dynamics) and the individual level (i.e., behavior, personal characteristics, contextual factors) (Chapter 2). In so doing, I offered a redefinition of the existing educational framework that defines learner engagement in order to account for specific aspects of learning networks emerging from learning with MOOCs. Specifically, following Reschly and Christenson (2012) research, I proposed a model for studying the association between context, learner engagement and learning outcome (Section 3.2). I further suggested that engagement in learning networks should be observed as a multi-dimensional construct, comprised of academic, behavioral, cognitive, and affective engagement.

Having a generally accepted conceptualization of engagement in learning networks should allow for obtaining consolidated insights into the factors that influence learning in networks emerging from learning with MOOCs and how these factors could be utilized in providing assessment for learning in networked settings (DeBoer et al., 2014). Established in existing research on learner engagement, the proposed operationalization affords basis for comparisons with diverse learning contexts such as con-

ventional online or face to face learning. Providing an analogy between different educational contexts would be particularly important for informing future designs and pedagogies for learning with MOOCs, establishing a more salient connection with existing learning theories and practices (Dawson *et al.*, 2015; Wise and Shaffer, 2015; Reich, 2015). Moreover, there is a general understanding in the existing MOOC literature that “effort is correlated with achievement” (Reich, 2015, p.34), however there is no clear causal evidence “between doing more and doing better” (Reich, 2015, p.34). Providing a common understanding of what engagement actually is and how it should be measured in this complex learning context, which seems to lack in the existing studies, should allow for advancing research on learning networks emerging from MOOCs. In particular, relying on definition and operationalization of engagement introduced in Chapter 3, creates an opportunity for measuring factors that promote learning beyond simply observing learners’ “click data” and exploring how quantity and quality of interactions with the course content, peers, and teaching staff could predict course outcome and persistence.

### 6.1.3 Empirical validations of the proposed model constructs (RQ3&RQ4)

The second part of my thesis focuses on the evaluation of the proposed conceptual model introduced in Chapter 2. In so doing, I conducted several empirical studies that introduce novel analytics methods for studying learning networks and for assessing and understanding learning (and teaching) in MOOCs. Each of the empirical studies presented in Chapter 4 and Chapter 5 observes more than one form of learner engagement (as introduced in Chapter 3) in explaining factors that drive network formation and contribute to knowledge building and sharing in learning networks emerging from various configurations of learning with MOOCs.

#### Factors that drive formation and structure of learning networks (RQ3.1)

Importance of examining network structure for revealing various aspects of learners’ interactions (e.g., who is talking to whom and who are the most influential learners) has been well-established in educational research in general, and studying learning in networks in particular (Eynon *et al.*, 2016; Jones, 2015). This thesis contributes to the existing research on learning networks that examines underlying factors that determine formation of networks in the context of learning with MOOCs. Specifically, focusing on *structural* and *temporal* dimensions of the conceptual model introduced in Chapter 2, I analyzed learning networks emerging from various social media (i.e., Twitter, Facebook, and blogs) used in a cMOOC (Section 4.2 and Section 4.3). Observing the evolution of network structure, the study introduced in Section 4.2 showed that over the MOOC progression, a group of nodes developed network positions comparable to those of course facilitators. This group of emergent influential nodes included both human participants and hashtags adopted in communication using the Twitter platform. The most prominent social and technical nodes further influenced development of several interest-based communities of learners, clustered around the same topics of interests. Therefore, one of the promising venues for future research and practice would be in investigating approaches to fos-

tering interactions between different communities, based on the potential similarities between the central nodes that the communities were formed around.

To account for *discourse* properties and provide a complementary perspective into understanding of personal and contextual factors that drive network formation, I further analyzed linguistic features of socially-shared content within a learning network emerging from a cMOOC. Here, I also accounted for temporal aspect of the emergence of observed linguistic structures (Section 4.3). The findings indicate that in order to better understand the development of network structures and providing means for the implementation of assessment for learning in networks, both shallow and complex discourse analysis are needed. Specifically, in addition to mutual interests in similar topics discussed online (Section 4.2 and Section 5.2), my findings also suggest that learners who were more centrally located in learning networks tended to share more mutual understanding during the communication. This finding highlighted the importance of the common ground (Brennan and Clark, 1996) shared between learners for explaining emerging structures of learning networks developed in the context of learning with MOOCs. As such, this finding goes along with the conceptualization of the analytics-based model introduced in Chapter 2 and directly contributes to the understanding that discourse, structure, and dynamics should be observed as mutually interdependent constructs in explaining learning networks. Moreover, from the perspective of future research, the study introduced in Section 4.3 argues for the importance of developing methods that would foster learners in networked settings to engage into the activities that would allow for establishing common ground (Wohn *et al.*, 2010).

Finally, studying social structures the existing research on learning networks primarily builds on the methods and approaches emerging from graph theory and social network analysis (Freeman, 1978). Although, the application of traditional (i.e., descriptive) social network analysis provides invaluable insights into understanding structure of learning networks (Wasserman, 1994; Eynon *et al.*, 2016), in my thesis I argue for the importance of complementing such analysis with statistical network analysis (Goodreau *et al.*, 2009). Statistical network analytics, in comparison to conventional social network analysis, allowed for deeper insights into social dynamical factors that drive formation of learning networks. For example, my findings showed that reciprocity of learners' interaction presents an important factor in the formation of learning networks. This finding indicates that learners tended to continue interacting with peers who had replied to their posts. The importance of creating reciprocal ties is also recognized in the literature focusing on a broader context of online learning, being indicative of learners' tendency to connect with their peers, creating a comfortable environment for knowledge sharing and learning (Lusher *et al.*, 2012). It is also indicative that learning networks emerging from learning with MOOCs tended to form around a tendency to establish ties based on homophily, which is also recognized as a "key organizing process for social networks" (McLeod *et al.*, 2014, p.552) in general. For example, studies introduced in Section 4.4 and Section 5.3 found a tendency for learners to form ties with peers who had similar demographic backgrounds (e.g., language used) or achievement (e.g., passed or failed a course), showing the importance of considering individual agency in

studying learning networks, as theorized in the conceptual model introduced in [Chapter 2](#). Finally, the findings also suggest that discussions in learning networks tend to cluster around small groups, denoting perhaps a high “modularity in communicative tendencies” (Gillani and Eynon, 2014, p.22) as a significant factor that frames structure of learning networks emerging from MOOCs. As argued by Gillani and Eynon (2014) or DeBoer *et al.* (2014), for example, the tendency of learners to engage into discussions around disperse groups, rather than communities, of learners has a significant practical implications for the way we define and measure participation in MOOCs.

#### **Structure as a mediating factor for understanding learning outcome (RQ3.2)**

As more thoroughly addressed in [Chapter 4.4](#) and [Chapter 5.3](#), it is important to consider factors that frame interactions in learning networks in order to provide salient understanding of the association between learner engagement and learning outcome. Specifically, understanding structure of learning networks is not only important for revealing most influential actors emerging in the process of knowledge building and sharing in networked settings or identifying processes that drive interactions in such settings. Understanding of social processes that frame learning networks is also important from the perspective of providing contextually salient understanding of the association between learning processes (operationalized through various dimensions of learners’ engagement) and learning outcome.

From the practical perspective, understanding the importance of emerging network structures for interpreting learning in MOOCs, could have significant implications for the implementation of assessment for learning and automated feedback provision. For example, informing learners and teachers about the learning process using analytics dashboards (Schreurs *et al.*, 2013) can be considerably improved by visualizing network structure using deeply embedded relations (i.e., Simmelian backbones) (Nick *et al.*, 2013). Moreover, providing learners and teachers with additional information about social dynamics that frame social interactions in learning networks, should supplement any type of formative feedback that relies on measures of structural centrality (e.g., degree or betweenness centrality) to predict learning outcome. Likewise, research that examines the association between (descriptive) network centrality measures and learning outcome should be constructed on valid theoretical assumptions that could support conclusions about inferred social dynamics. Observing structure as a mediating factor in understanding learning outcome in learning networks, thus goes in line with the assumptions introduced in [Chapter 2](#). Specifically, examining social dynamical processes that drive formation of learning networks further represents a context defined through the collective behavior that is specified by a general social situation in a given settings.

#### **Processes of knowledge construction in learning networks (RQ4.1)**

Understanding learner generated discourse, in terms of examining topics being discussed or processes employed in knowledge building and sharing, have been recognized as one of the important aspects of research on learning networks emerging from MOOCs (Eynon *et al.*, 2016; Goodyear, 2004). Contributing to this line of research, the present thesis (and particularly [Chapter 5](#)) employs various



learning analytics methods and approaches to examining processes of knowledge construction as being reflected through the learner generated discourse, thus providing means for the implementation of assessment for learning in networks. Finding from the study presented in [Section 5.2](#) suggest general tendency for learners in networked settings to focus on topics of their personal interests, not necessarily following themes being introduced through the course design (Siemens, 2005). However, the importance of media used, as to interact with peers had a significant impact on how learners discussed certain topics. Specifically, it seems that differences in affordances provided within various social media (e.g., Twitter, Facebook, blogs), represent an important context for interpreting processes of knowledge construction in learning networks ([Chapter 2](#)).

Building on the speech acts theory (Searle, 1976) my research further examined learner intents, expressed through language and discourse, that characterize communication in learning networks emerging from learning with MOOCs. Thus, the study introduced [Section 5.3](#) revealed six overarching categories of speech acts that capture communication intents within the networks of learners, categorized as three subcategories of *Directive* speech acts (questions & answers, instruction, and elaboration), *Expressives*, *Representatives*, and a category of messages that could not be characterized as any act of speech, and thus was labeled *Other*. The findings further suggest that learners in MOOCs tend to start discussions primarily employing expressive speech acts, as means to establish a social connection with their peers (Garrison and Akyol, 2013; Poquet and Dawson, 2016). Moreover, findings suggest that a majority of discussion threads tended to converge towards the category of posts that includes higher learner-teacher interaction, with the primary intent to communicate problems learners encountered and provide solutions to those (i.e., Directives questions & answers). From the practical perspective, the approach presented here, could provide teachers with valuable information about learner participation in a discussion forum. For example, relying on the proposed approach, teachers could obtain a comprehensive (automated) summary of discussion threads learner are involved with, which could further allow for a more advanced feedback provision than present tools offer. These finding further contribute the understanding of considering learner generated discourse, as one of the determining dimensions of learning networks, as being situated within a specific learning context ([Chapter 2](#)).

#### **Knowledge construction and shared meaning as factors that shape learning networks (RQ4.2)**

As theorized in the proposed conceptual analytics-based model ([Chapter 2](#)), structure, discourse, and dynamics of learning networks should be observed as mutually dependent constructs. Therefore, the study presented in [Section 5.3](#) also examined the association between discourse properties and structure of social interactions that drive formation of networks in learning with MOOCs. The study showed that different conversational patterns evident in the learners' contributions to the discourse generated in the social interaction within the network of learners revealed rather distinct social dynamics that framed emerging social networks. Specifically, discourse characterized by rather homogeneous threads (in terms of speech acts employed in communication), primarily focused on Q&A sessions, and with a substantial common ground shared between learners, is associated with the evo-

lution of networks characterized by qualitatively stronger interactions between peers (Krackhardt, 1999).

One of the notable differences with respect to the communication patterns observed in the two examined learning networks, and potential implications for further research, is related to the patterns of teachers' participation. Learning networks emerging from MOOCs are being learner-centered and heavily depend on learners' motivation to engage and regulate their learning (Jones, 2015). However, the findings from the study introduced in Section 5.3 suggest that the formation of small, highly cohesive groups, (i.e. groups characterized by super-strong ties) (Krackhardt, 1999) might depend on the presence and role of the teacher (Garrison and Akyol, 2013; Jones, 2015; Laat *et al.*, 2007). From the perspective of the assessment for learning in networks, the proposed conceptual model (Section 2), and particularly the operationalization of the model constructs introduced in Section 3, argue for the importance of considering various contextual factors (e.g., course design, assessment practices) (Section 3.2). In that sense, De Laat *et al.* (2007), for example, recognize novice and experienced online teachers, suggesting further the importance of considering teachers' experience as a significant factor that could have implications for designing for learning in networked settings.

## 6.2 Methodological contributions and their implications

There are several methodological contributions of the work presented in this thesis. Specifically, in order to provide an empirical validation for the proposed conceptual analytics-based model (Chapter 2), throughout the five studies introduced in Chapter 4 and Chapter 5, I proposed several approaches to studying learning networks. In the following subsections, I discuss methodological contributions with respect to the methods used to evaluate key constructs necessary for understanding learning networks - discourse, structure, and dynamics (Chapter 2).

### 6.2.1 Methods and approaches to studying formation and structure of learning networks

The study introduced in Section 4.2 adopts a socio-technical perspective (Jamali and Abolhassani, 2006) in exploring aspects that define structure and formation of learning networks. Specifically, modeling learning network formed around a cMOOC from the socio-technical perspective, I was able to observe technological and social dimensions as mutually constituted. The study further combined methods of traditional social network analysis, observing changes in structural centrality measures over the course progression, with a community detection analysis (Newman, 2006), to identify roles that social and technical nodes occupied in the information flow and learning network formation. Demographic data collected about social nodes (i.e., learners) were further utilized to interpret identified network communities and explain the factors that influenced their formation.

Learning in networks, however, usually includes utilization of various social media (Siemens, 2008). From the methodological perspective, the application of social network analysis and the inclusion of

multiple technologies pose numerous challenges. For example, it is questionable whether social (or socio-technical) learning networks should be analyzed separately within each of the media used, or perhaps creating a single course-level network that would include learners' interactions within all the media. Moreover, it is also important to consider whether the links from different media should be weighted differently. Finally, the integration of learners identified from different social media can be a challenge and can pose a threat to the validity.

Section 4.3 further introduces a research that investigates factors, such as language used and available media affordances, and their association with the development of social capital, as a form of learning outcome in learning networks (Section 3). Being theoretically rooted in the network theory of social capital (Lin *et al.*, 2001), this study (Section 4.3) provides an operationalization of social capital through the measures of network centrality as commonly used in social network analysis. Further, to analyze discourse patterns on multiple levels (including genre, cohesion, syntax, words), I used Coh-Metrix, arguably the most comprehensive automated linguistic analysis tool (Dowell *et al.*, 2016; Graesser *et al.*, 2011). Finally, I applied advanced statistical modeling in order to examine the association between language and media used with the developed social capital. One of the significant implications of this work suggests that linguistic analysis methodologies can be leveraged to determine a learner's position within a learning network and further used to help foster peer connections. However, further investigations need to examine the "characteristics" of individual learners that not only increase the development of social capital but also the mobilization of social capital for a specific return (i.e., learning outcome in this case).

### 6.2.2 Methods and approaches to studying discourse generated in learning networks

The second part of the empirical evaluation of the proposed conceptual analytics-based model introduced in Section 2, primarily focuses on aspect of studying discourse generated in learning networks. In order to examine various knowledge building and sharing processes reflected in learner generated discourse and to what extent discourse shapes structure of learning networks, the present thesis provides two broad methodological contributions.

To gain insights into learning processes occurring within a network of learners and examine the most prominent themes discussed across different social media platforms, the study introduced in Section 5.2 introduces novel approach to topic modeling. Specifically, combining techniques for semantic annotation and graph analysis with a qualitative analysis of learner-generated discourse, I examined how social media platforms (i.e., blogs, Twitter, and Facebook) and course recommendations influence content creation and topics discussed within a network of learners. One of the main contribution of this approach is that it offers a scalable method for extracting emerging topics providing a list of keywords that describe identified themes. For example, the most commonly used approaches to topic modeling, such as Latent Dirichlet Allocation (LDA) (Blei *et al.*, 2003), provide a list of simple terms

(e.g., “network”, “social”) in describing topics, that are not necessarily easy to interpret in the context of observed topic. The approach proposed in [Section 5.2](#), on the other hand, provides a more comprehensive list of extracted keywords (e.g., “social networks analysis”, “networked learning”) that, combined with an in-depth qualitative analysis, enable more straightforward understanding of underlying themes being discussed. In addition to allowing for validating certain ideas of connectivism, from the practical perspective, the approach introduced in [Section 5.2](#) might be suitable for the analysis of different media applied to designing for learning in networks, as one of the critical features. For such multi-media studies, it is essential to proceed to the analysis of actual content and discourse rather than just counts of the us ([Mak et al., 2010](#)). Being able to reveal topics discussed in different media and among emerging social groups might help learners to “bridge the social gap” and more easily reach groups of learners with similar interests.

The study introduced in [Section 5.3](#) presents, arguably, the most prominent way to integrating discourse and social network analysis that also allows for understanding of sequence of actions employed in communication. In this study ([Section 5.3](#)), I primarily grounded the theoretical framework in the speech acts theory ([Searle, 1976](#)), as means for investigating intended meaning (i.e., speech act) of the discourse generated through communication in learning networks. Relying on unsupervised methods for discourse analysis, namely block hidden Markov models [Paul \(2012\)](#), I was able to identify, in an automated way, common groups of speech acts emerging from discussion forums of the two MOOCs analyzed. One of the main benefits of using the unsupervised approach to analyzing learner generated discourse in learning networks emerging from MOOCs is that it does not require manual coding. This allows for implementing scalable approaches for assessment for learning in MOOCs.

Finally, based on the findings from the study introduced in [Section 5.3](#), it is also indicative that different conversational patterns evident in the learners’ contributions to the studied discussion forums revealed rather distinct social dynamics that framed emerging social networks (as more thoroughly explained in addressing Research Question 4.1). One of the methodological challenges stemming from the applied approach is the identification of an optimal unit of analysis that would provide more comprehensive insights into speech acts employed in communication. Even though speech acts analysis at the message level provides useful insights into conversational dynamics, as confirmed in this and previous studies ([Arguello and Shaffer, 2015](#); [Merceron, 2014](#)), further research should explore approaches that use individual utterances as a unit of analysis. Such an approach would provide more fine grained insights into emerging conversational patterns.

### 6.3 Moving forward

My future research efforts will be primarily guided towards extending ideas presented in the proposed analytics-based model and strengthening operationalization of dimensions used to understand learning networks. Specifically, my goal is to introduce more sophisticated methods for studying *discourse* ([Chapter 2](#)) and measuring *cognitive* and *affective* engagement ([Chapter 3](#)). Moreover, building on the

findings from the present thesis, I will also develop an implementation of the proposed model to enable assessment for learning in MOOCs.

The main goal of the research presented in [Chapter 5](#) was to provide insights into the importance of understanding learner generated discourse and connection between discourse and structure as learning unfolds. However, building on the current work in the automated content analysis of MOOC discussion forums, there is a potential to extend the dimensions used to understand discourse. For example, Kovanovic and colleagues (2016) developed methods for automated content analysis according to different levels of cognitive presence. As part of the Community of Inquiry model (Garrison *et al.*, 2001), a widely-used and well-developed pedagogical framework for studying learning in online educational settings, cognitive presence captures learners' development of critical and deep thinking skills (Garrison *et al.*, 2001). As such, cognitive presence presents one of the promising dimensions that could provide comprehensive insights into learners cognitive engagement and understanding of quality of discourse generated in learning networks.

Another promising line of research in broadening understanding of discourse and knowledge building in learning networks represents operationalization of different dimensions of epistemic tasks (Ohlsson, 1996; Jones and Steeples, 2002; Goodyear, 2002). Ohlsson (1996), for example, proposed a framework that outlines taxonomy of epistemic tasks to “cast aspects of understanding into the language of discourse and action” (Goodyear, 2002, p.62). Thus, relying on the methods of the epistemic network analysis (Shaffer *et al.*, 2009), I will provide more holistic means for evaluating online discourse and understanding of the collaborative knowledge building. Likewise, the extension of the study introduced in [Section 5.3](#) will focus on building epistemic networks relying primarily on speech acts extracted from interaction in learning networks.

Although the importance of the emotional learning analytics attained a significant attention recently (D'Mello, 2017; D'Mello *et al.*, 2017), there is little research that utilizes any of the existing approaches for affect detection in the context of learning networks emerging from learning with MOOCs. Such a line of research would allow further to provide holistic methods for measuring *affective engagement* and *affective learning outcome* that results from engagement in learning networks ([Chapter 3](#)). In one of the recent studies, Bosch and D'Mello (2017), for example made a considerable advances in mapping affective states, such as anger, anxiety, boredom, confusion, curiosity, disgust, fear, frustration, flow/engagement, happiness, sadness, and surprise to the traces of learner interactions in online settings. Triangulating data from students' face recordings, self-reports, and trace data, (Bosch and D'Mello, 2017) detected certain behaviors (e.g., reading, coding) that trigger specific affective states (e.g., boredom, engagement, curiosity, frustration). Although still in its infancy, such research provides a sound basis for more salient operationalization of affective engagement and affective outcome, as operationalized in [Chapter 3](#).

The proposed conceptual analytics-based framework for studying learning networks should allow for implementation of learning analytics as a part of pedagogy, thus enabling assessment for learn-

ing with MOOCs. Specifically, [Eynon et al. \(2016\)](#) and [Reich \(2015\)](#), among others, argue for the importance of experimentation for providing causal relationships between learning related constructs and learning in networked settings. [Eynon et al. \(2016\)](#), for example, goes further proposing an email based intervention to explore how and to what extent different recommendations foster learner social engagement. Learners were randomly assigned to different groups at the beginning of the course, and remained in those groups until the end of the course. Building on the framework introduced in one of our recent studies ([Kovanović et al., 2017](#)), my colleagues and I are developing a platform that would allow for (almost) real-time experimentation with learning networks emerging from learning with MOOCs. The platform should allow for implementation of various aspects introduced in this thesis and identification of potential treatment groups during the course, based on various engagement metrics. Such an approach should result in a software platform for the analysis of data obtained from learning in networks, that focuses on conducting data-informed instructional interventions and experimentations in the context of learning networks as learning unfolds ([Kovanović et al., 2017](#)).

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# Appendix A. Supplementary material

The present Appendix includes a copy of the supplementary material for the study introduced in [Section 3.2](#). Publicly available version can be found at the following link:

[http://sjoksimovic.info/files/mls\\_supplementary\\_material\\_v1\\_1.pdf](http://sjoksimovic.info/files/mls_supplementary_material_v1_1.pdf)

## **How do we Model Learning at Scale? A Systematic Review of the Literature – *Supplementary material***

Version 1.1

**Explanatory Note:** This document supplements the manuscript entitled “How do we Model Learning at Scale? A Systematic Review of the Literature”.

Figure S1 provides an overview of the Reschly and Christensen’s original model (2012) of the association between contextual factors, student engagement, and desired learning outcomes.

Table S1 presents an Overview of the attributes that comprise the coding scheme used in the literature review. For each of the attributes we also provided a brief description and list of potential values (if appropriate)

Table S2 provides a list of the studies included in the literature review along with the overview of learning outcomes used in each of the studies. For each study, we also provided a definition and description of the outcome measured.

Table S3 presents a comprehensive list of metrics used to measure and understand learning in studies included in the analysis. Each metric is accompanied with the its definition, information about the latent construct assigned, and the list of studies that extracted given metric.

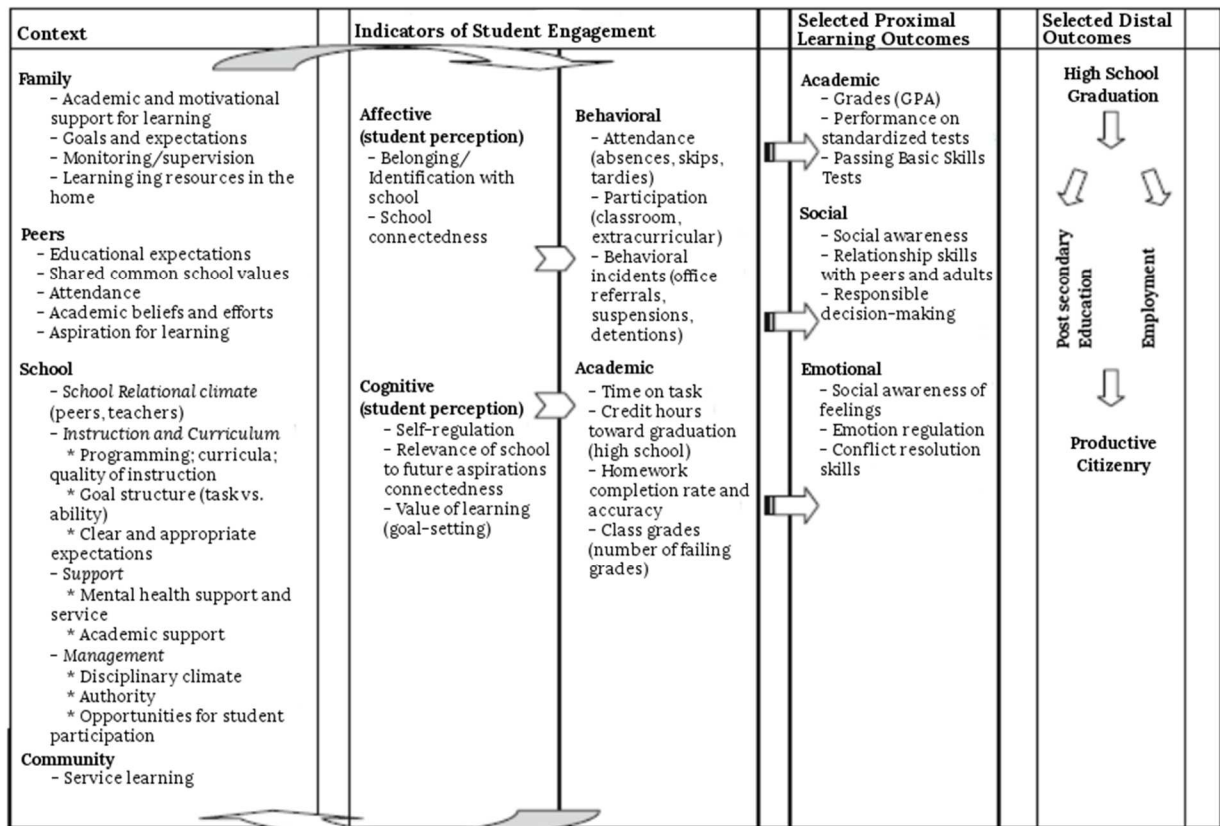


Fig. S1. The original model of association between context, engagement and outcome, as defined in Reschly and Christenson's study (2012, p.10).

Table S1. Overview of the attributes that comprise the coding scheme used in the review

Attribute	Description
Author(s)	
Title	
Publication year	
Publication venue	
Coder	Name of the coder who coded a study.
Study ID	Unique identifier for a study.
Adopted theory	Indicates the theory used in the coded study.
Study objective	Indicate study objective.
Exploratory/ Confirmatory	Indicates whether study is exploratory or confirmatory.
Platform	Indicate platform(s) used for MOOC delivery (e.g., edX, Coursera).
Education level	Indicate the level of education study focuses on (e.g., K-12, HIGHER_EDUCATION, ADULT_EDUCATION).
Students registered	Count of students registered per each course analyzed. “NR” if not reported.
Students active	Count of active students per each course analyzed. “NR” if not reported.
Students certificate	Count of students who obtained a certificate, per each course analyzed. “NR” if not reported.
Courses per domain	Count of courses analyzed, per domain (e.g., TECHNICAL, SOCIAL).
Course offer certificate	Count of courses analyzed that offer a certificate.
Courses per design	Count of xMOOC and/or cMOOC courses.
Data source	Indicate the data sources (e.g., surveys, trace data).
Outcome variable	Indicate outcome variables measured.
Outcome variable definition	Indicate the definition of the outcome variable, as defined in a study.
Predicting variable(s)	Indicate independent variables defined within a study. For each predictor we want to code observed variable, latent variable and how this variable was measured.
Predicting variable(s) definition	Indicate definition for each of the independent variables used.
Confounders	Indicate confounders identified within the coded study.
Analysis focus	Indicate whether study focuses on all students enrolled in a course, or a specific subgroup (e.g., ALL_STUDENTS or COMPLETED_ONLY)
Statistical model	Indicate statistical/machine learning method used in the study (e.g., SEM, MIXED_MODELS).
Statistical model definition	Indicate details of a statistical model specification.
Statistics	List statistics for the main results. Specifically, report the model properties, such as p-values, r squared, AICc.
Predictors statistics	Report all the relevant statistics for predictors. Likewise, the previous field, name of the statistics should be listed along with a value
Results – summary	Indicate main results, as listed in a study.
Main findings	Indicate main findings, as listed in a study.
Implications	Indicate main implications, as listed in a study.
Limitations reported	Indicate whether limitations were reported or not (YES/NO).
Generalizability reported	Indicate whether study discusses potential generalizability of the findings (YES/NO).
Pedagogical factors considered	Indicate whether study considers pedagogical factors when analyzing – interpreting results (YES/DOES_NOT_APPLY/NOT_REPORTED)
Contextual factors considered	Indicate whether study considers contextual factors when analyzing – interpreting results (YES/NO).

Table S2. Overview of the learning outcomes measured as means for measuring learning in MOOCs, as operationalized in studies included in the review

Study Name	Learning Outcomes (author used terms)	Operationalization
<b>1) Academic Completion</b>		
Bergner et al. (2015)	Performance	Final exam score
Coffrin et al. (2014)	Final grade	Final course grade
Crossley et al. (2015)	Student success	Completion was a variable of success, and it was pre-defined as earning an overall grade average of 70% or above
Koedinger et al. (2015)	Drop-out Learning	Final exam participation Quiz scores and final exam score
Ramesh et al. (2014a)	Learner performance Survival (of a phase of the course)	Receiving the statement of accomplishment
Tucker et al. (2014)	Student performance and learning outcomes	Grades attained in course assignments, quizzes and examinations
X. Wang et al. (2015)	Learning Gains	Standardized exam score
Brooks, Thompson, et al. (2015)	Student success	Earning a certificate of completion
Sharma et al. (2015)	Success and failure through engagement and performance	Drop-out vs. completion (both normal and distinction)
Kennedy et al. (2015)	Success MOOC performance	“Total points” a measure of students’ overall performance in a course, and was calculated as the cumulative points earned by the learner across all assignments on the final day of the course
Sinha and Cassell (2015)	Student Performance	Final Grade
Adamopoulos (2013)	Student retention Student satisfaction	Self-reported progress of each student in each course, completed, partially completed or successfully completed The sentiment of the individual review for the professor
Engle et al. (2015)	Achievement level equaled to the course success	Achievement level was measured from the students who filled in pre-survey, and these were divided into 5 groups (did not complete any exams; completed some exams, but not all; completed all exams without passing the course; passed the course without distinction; passed the course with distinction)



Study Name	Learning Outcomes (author used terms)	Operationalization
Gillani and Eynon (2014)	Final marks	Final course mark
Jiang, Warschauer, et al. (2014)	Performance	Performance was defined as the types of certificate the learner achieved (normal or with distinction; or not at all).
Greene et al. (2015)	Retention Achievement	“Retention was measured by the completion of the week’s end of unit exam”. (p.940) “Achievement was operationalized as total exam grades, which was the sum of all course scores” (p.940).
<b>2) Cognitive Change</b>		
Champaign et al. (2014)	Skill improvement	Combined skill on homework and test quizzes. Skill = item response theory
Konstan et al. (2015)	Learning gains (normalized subject matter learning gains)	20-item instructor-generated pre- and post- class knowledge test to measure gains (normalized due to the differences between the sample who took pre- and post- tests)
Li et al. (2015)	Completion Perceived video difficulty	Completing the 6 <sup>th</sup> writing assignment and the third part of exam 2. Subjective in-video posterior evaluations inquiring about the easiness of understanding the content in the video
<b>3) Persistence and Drop-out</b>		
Whitehill et al. (2015)	Drop-out/Stop-out	Student does not earn a certificate, and takes no action between time t and the time when certificates are issued. (my note: in other way, is inactive); disengages, drops-out.
Ye et al. (2015)	Drop-out	If in a given week a student accessed fewer than 10% of the remaining lectures and performed no further assessment activities; and all students characterized as dropped out in w1, dropped out in w 2, dropped out in w 3, and not dropped out by the end of week 3.
Heutte et al. (2014)	Persistence	Return to the platform
Vu et al. (2015)	Social Learning Performance Learning success	“social and temporal” structure quiz grades drop-out
Boyer and Veeramachaneni (2015)	Persistence (vs stop-out/ drop-out)	A learner was said to persist in week if s/he attempts at least one problem presented in the course during the week
Santos et al. (2014)	Success and Failure	Drop-out vs. completion
Loya et al. (2015)	Completion	Completion either meant submitting all assignments, or was a combination of some assignments combined with video viewing metrics.
<b>4) Social Aspects of Learning</b>		
Wen et al. (2014b)	Drop-out from forum discussion	Student does not post any more

Study Name	Learning Outcomes (author used terms)	Operationalization
Wen et al., (2014a)	Drop-out from forum discussion	Student does not post any more
Authors (2015b)	Academic performance	Student performance is represented by the final course grade (an aggregate measure combining scores for the essays submitted during the MOOC, and a final peer-evaluated, open-ended written-assignment).
	Social centrality	Social centrality is represented by degree, betweenness, closeness and eigenvalue in directed weighted networks.
Authors (2015a)	Social Capital Accumulation	Learner centrality measures in learning networks emerging from interactions in social media
Goldberg et al. (2015)	Completion Forum engagement	Number of posts
	Completion rates	No completion - a learner did no evaluative exercises or did not pass the course threshold for minimum grade; Normal completion – a user achieved a grade above 80% but below 95%.
Brooks, Stalburg, et al. (2015)	Sociability	Distinction – a user achieved a grade 95% or above. The mean number of postings per user.
	Social Positioning Attainment measures	Degree, betweenness and closeness as random or not. Final grade
<b>5) Multi-dimensional measures</b>		
Kizilcec and Schneider (2015)	Learner behavior:	A set of behavioural measures that capture learners' progress in the course, their general performance, and social engagement on discussion forums.
	a) progress in the course	Behavioural measures captured learner's progress in the course, their general performance, and social engagement.
	b) general performance	a) progress in the course quantified by 3 milestones for the proportion of the watched videos and the proportion of the attempted assignments (the learner attempted more than 10%; 50%, 80%) of lecture videos.
	c) social engagement	b) receiving a certificate of completion c) two measures of activity on discussion forums and a measure of endorsement by the learner community: the learner authored one or more posts/comments on the discussion forum; the learner authors over half as many posts as the most prolific poster, and the learners received one or more net votes.
	Attrition	Persistence
Kizilcec and Halawa (2015)	Persistence	Probability of achieving the following milestones: watching (or downloading) over 30%, 50%, 80% of lecture videos; attempting over 30%, 50%, 80% of assessments.
	Achievement	Achieving a grade above the 60 <sup>th</sup> , 80 <sup>th</sup> percentile.
	Satisfaction	Learner self-reported – was satisfied learner a successful learner, or was
	Relative progress Relative satisfaction	

Table S3. The list of the metrics used to model learning in MOOCs, extracted from the studies included in this systematic review, along with the categorization according to different engagement types.

Latent construct	Metric	Definition	Study(ies) include
<b>Academic engagement (AcE)</b>			
AcE	last_quiz	Capture the time-period in which each last interaction of the user occurred. These features measure to what lengths the user participated in different aspects of the course (start, mid, and end)	Ramesh et al. (2014a), Ramesh et al. (2014b)
AcE	last_lecture	Capture the time-period in which each last interaction of the user occurred. These features measure to what lengths the user participated in different aspects of the course (start, mid, and end)	Ramesh et al. (2014a), Ramesh et al. (2014b)
AcE	last_post	Capture the time-period in which each last interaction of the user occurred. These features measure to what lengths the user participated in different aspects of the course (start, mid, and end)	Ramesh et al. (2014a), Ramesh et al. (2014b)
AcE	last_view	Capture the time-period in which each last interaction of the user occurred. These features measure to what lengths the user participated in different aspects of the course (start, mid, and end)	Ramesh et al. (2014a), Ramesh et al. (2014b)
AcE	last_vote	Capture the time-period in which each last interaction of the user occurred. These features measure to what lengths the user participated in different aspects of the course (start, mid, and end)	Ramesh et al. (2014a), Ramesh et al. (2014b)
AcE	baseline_knowledge_test_score	A score on the baseline knowledge test	Konstan et al. (2015), Koedinger et al. (2015)
AcE	number_of_written_assignments	A total number of submitted written assignments	Konstan et al. (2015)
AcE	number_of_programming_assignments	A total number of submitted programming assignments	Konstan et al. (2015)
AcE	amount_of_course_completed	Amount of the course completed, relative to expectations	Konstan et al. (2015)
AcE	first_submission_score	A score achieved at the first submitted assignment	Sharma et al. (2015)
AcE	first_action_week	A week when student started course interaction	Sharma et al. (2015)
AcE	activity_span	The difference in weeks between the first activity (as described in the previous item) and the last activity	Sharma et al. (2015)
AcE	progress_within_programming_assignments	The difference between the two consecutive submissions for the same assignment, as a proportion of maximum attainable score for each assignment. Average number of attempts for each programming assignment	Sharma et al. (2015)
AcE	procrastination_index	The ratio of the time difference between the submission time and the hard deadline and time difference between assignment being posted online and the hard deadline	Sharma et al. (2015), Boyer and Veeramachaneni (2015)

Latent construct	Metric	Definition	Study(ies) include
AcE	relative_time_through_course	The relative time through the course ( $t = T_e$ )	Whitehill, et al. (2015)
AcE	elapsed_time_between_previous_activity_and_time_t	The elapsed time between the last recorded event and time t	Whitehill, et al. (2015)
AcE	student_grade_at_t_relative_to_certificate	The student's grade at time t relative to the certification threshold ( $gt=G$ )	Whitehill, et al. (2015)
AcE	has_enough_points_to_certify	Binary feature encoding whether the student already has enough points to certify ( $[I_{gt} \geq G]$ )	Whitehill, et al. (2015)
AcE	average_first_lecture-embedded_quiz_answer_time	The offset between the time the lecture became available and the time the student first answered an embedded quiz question in the lecture	Ye et al. (2015)
AcE	difference_between_average_first_lecture-embedded_quiz_answer_time_for_the_current_week_versus_the_previous_week	Difference between average first lecture-embedded quiz answer time for the current week versus the previous week	Ye et al. (2015)
AcE	the_total_number_of_lecture-embedded_quiz_questions_answered	The total number of lecture-embedded quiz questions answered	Ye et al. (2015)
AcE	average_number_of_times_a_lecture_was_accessed_before_the_first_lecture-embedded_quiz_question_was_answered	Average number of times a lecture was accessed before the first lecture-embedded quiz question was answered	Ye et al. (2015)
AcE	average_number_of_times_the_lecture_was_accessed_after_the_first_lecture-embedded_quiz_question_was_answered	Average number of times the lecture was accessed after the first lecture-embedded quiz question was answered	Ye et al. (2015)
AcE	average_first_access_time_of_lectures	The offset between the time the lecture became available and the time the student first accessed the lecture	Ye et al. (2015)
AcE	prior_ability	Estimated prior ability levels from performance on homework assignments in the first three weeks of the course, when enrollees had just begun to learn the content and before discussion forum use had taken off	Bergner et al. (2015)
AcE	total_time_spent_on_all_resources	The total time spent on all course resources	Boyer and Veeramachaneni (2015)
AcE	number_of_distinct_problems_attempted	The total number of distinct problems attempted	Boyer and Veeramachaneni (2015)
AcE	number_of_submissions	The total number of problem/assignment/quiz submissions	Boyer and Veeramachaneni (2015), Brooks, Thompson, et al. (2015), Champaign et al. (2014), Kennedy et al. (2015)
AcE	number_of_distinct_correct_problems	A number of distinct correct problems submitted	Boyer and Veeramachaneni (2015)
AcE	average_number_of_submissions_per_problem	Average number of submissions per problem	Boyer and Veeramachaneni (2015)
AcE	ratio_of_total_time_spent_to_number_of_distinct_correct_problems	Ratio of total time spent to number of distinct correct problems	Boyer and Veeramachaneni (2015)

Latent construct	Metric	Definition	Study(ies) include
AcE	duration_of_longest_observed_event	Duration of longest observed event	Boyer and Veeramachaneni (2015)
AcE	total_time_spent_on_lecture_resources	Total time spent on lecture resources	Boyer and Veeramachaneni (2015)
AcE	total_time_spent_on_book_resources	Total time spent on book resources	Boyer and Veeramachaneni (2015)
AcE	total_time_spent_on_wiki_resources	Total time spent on wiki resources	Boyer and Veeramachaneni (2015)
AcE	number_of_correct_submissions	Number of correct submissions	Boyer and Veeramachaneni (2015)
AcE	percentage_of_the_total_submissions_that_were_correct	Percentage of the total submissions that were correct	Boyer and Veeramachaneni (2015)
AcE	ratio_of_number_of_problems_attempted_to_number_of_distinct_correct_problems	Ratio of number of problems attempted to number of distinct correct problems	Boyer and Veeramachaneni (2015)
AcE	total_frequency_of_accesses_per_resource_type	Total frequency of access per resource type (e.g., video)	Champaign et al. (2014)
AcE	the_total_time_spent_per_resource	The total time spent per resource	Champaign et al. (2014)
AcE	problem_submissions_correctness	quiz/test and homework problem submissions - whether problem was answered correctly	Champaign et al. (2014)
AcE	active_days	A measure of the total number of days a student was actively submitting assignments in the course	Kennedy et al. (2015)
AcE	assignment_switches	Measure of the number of times a learner switched from submitting one assignment to a different assignment	Kennedy et al. (2015)
AcE	average_quiz_score_first_week	The average quiz score learners obtained in the first week of the course. There are four quizzes in Unit 1 and the quiz score ranged from 0 to 6	Jiang, Warschauer, Williams, O'Dowd, and Schenke (2014)
AcE	number_of_peer_assessment	The number of peer assessments students completed in Week 1	Jiang, Warschauer, Williams, O'Dowd, and Schenke (2014)
AcE	pretest_participation	A binary variable indicating whether student took pretest or not	Koedinger et al. (2015)
AcE	quiz_participation	Whether student participated in a quiz	Koedinger et al. (2015)
AcE	quiz_score	Average quiz score	Koedinger et al. (2015)
AcE	total_quiz_score	Sum of all quiz scores by a student	Koedinger et al. (2015)
AcE	user_active_time	The gap between the current time and the enter time of a learner which is used to control for the cohort effect.	Vu et al. (2015)
AcE	user_quiz_recency	The gap time between the current time and the last quiz submission time which is included to model the recency effect or the clustering of submission events over time.	Vu et al. (2015)
AcE	user_quiz_scores	The cumulative score of three graded quizzes that a learner has received	Vu et al. (2015)
AcE	user_pass_achievement	An indicator that is equal to 1 if user quiz scores is greater than 20. It is used to control for the scenario that learners cease the class after achieving the assessment threshold.	Vu et al. (2015)

Latent construct	Metric	Definition	Study(ies) include
AcE	user_current_quiz_score	The best score on a quiz that a learner has received.	Vu et al. (2015)
AcE	thread_degree_and_quiz_scores	This interaction between thread degree and user quiz scores to differentiate the popularity of a thread further based on quiz performance of learners who have contributed to it.	Vu et al. (2015)
AcE	assignment_grades	Grades on the assignments in the first two weeks of the course	Vu et al. (2015)
AcE	user_video_view_time	The total time that a learner has spent on watching video lectures.	Vu et al. (2015)
<b>Behavioral engagement (BE)</b>			
BE	count_of_all_activities	Count of all learning activities	Santos et al. (2014)
BE	count_of_questionnaire_activities	Count of activities for students who took questionnaire	Santos et al. (2014)
BE	participation_in_active_thread	Participation in thread that have more posts	Santos et al. (2014)
BE	bursty_number_of_play_video_events	unusually high rates of play video interaction	Sinha and Cassell (2015)
BE	bursty_number_of_chapters	unusually high rates of chapters read interaction	Sinha and Cassell (2015)
BE	bursty_number_of_discussion_forum_posts	unusually high rates of discussion forum posts	Sinha and Cassell (2015)
BE	poster_profile	This nominal variable categorizing users into active poster and inactive poster. If a user has more than 3 posts (including 3), he/she is categorized as an active poster, otherwise categorized as an inactive poster (3 is the median of the number of posts).	Wang et al. (2015)
BE	post_activity	Calculated for each user by assessing whether the user posts more than the average number of posts generated by all users	Ramesh et al. (2014a), Ramesh et al. (2014b)
BE	vote_activity	calculated for each user by assessing whether the user posts more than the average number of posts generated by all users	Ramesh et al. (2014a), Ramesh et al. (2014b)
BE	view_activity	calculated for each user by assessing whether the user posts more than the average number of posts generated by all users	Ramesh et al. (2014a), Ramesh et al. (2014b)
BE	reputation	represents whether the overall reputation of a user is above average	Ramesh et al. (2014a), Ramesh et al. (2014b)
BE	posts	capture an instance-level log of users posting on the discussion forums. The predicate posts take value 1 if the USER posts.	Ramesh et al. (2014a), Ramesh et al. (2014b)
BE	votes	capture an instance-level log of users voting on the discussion forums. The predicates votes take value 1 if the USER votes on POST.	Ramesh et al. (2014a), Ramesh et al. (2014b)
BE	upvote	Predicate upvote(POST) is true if the post has positive votes and false otherwise	Ramesh et al. (2014a), Ramesh et al. (2014b)
BE	downvote	predicate downvote(POST) is true if a post has been downvoted	Ramesh et al. (2014a), Ramesh et al. (2014b)
BE	number_of_forum_posts	Number of forum posts (total number of posts and/or weekly patterns)	Konstan et al. (2015), Wang et al. (2015), Crossley et al. (2015), Engle et al. (2015), Gillani and Eynon (2014), Goldberg et al. (2015), Vu et al. (2015), Santos et al. (2014)

Latent construct	Metric	Definition	Study(ies) include
BE	number_of_pauses	Frequency of pausing videos	Li et al. (2015)
BE	median_duration_of_pauses	The study uses median statistic for pauses because it is more robust compared to the mean and sum statistics for the highly skewed, long-tail distribution of the pause duration data	Li et al. (2015)
BE	number_of_forward_seeks	Frequency of using forward seeks	Li et al. (2015)
BE	proportion_of_skipped_video_content	The proportion that is skipped by forward seeks	Li et al. (2015)
BE	number_of_backward_seeks	Frequency of using backward seeks	Li et al. (2015)
BE	replayed_video_length	The length of replayed video	Li et al. (2015)
BE	average_video_speed	Refers to the weighted arithmetic mean of the video speeds at all video seconds	Li et al. (2015)
BE	effective_video_speed_change	The average amount of speed change during the video session	Li et al. (2015)
BE	delay_in_watching_lectures	The time difference in weeks, between the time when the video was released online and the time the students watched it for the first time	Sharma et al. (2015)
BE	participation	This is a binary variable indicating whether the student has ever posted in the discussion forum during the course.	Wang et al. (2015)
BE	on_task_percent	Percentage of "on task" posts - On-task discourse includes posts that talk about course content, the content of quizzes and assignments, comments on course materials, and interaction between students on course content-related issues	Wang et al. (2015)
BE	total_number_of_events_of_different_types_up_to_time_t	The total number of events of different types that were triggered by the student up to time t, where event types includes forum posts, video plays, etc.	Whitehill, et al. (2015)
BE	1D_temporarily-local_band-pass_filters	Gabor filters – 1D temporarily local band pass filters	Whitehill, et al. (2015)
BE	clickstream_behavior	Based on clickstream data, the study distinguishes instances where students are taking quizzes (quiz), watching lectures (lecture), participating in forums (forum), and viewing other course materials (course). The complete record of click behaviors within a 3-hour window before the student has made a post are collected to analyze patterns that might be associated with confusion. N-grams of behaviors, with a maximum length of 4, are then extracted from these collections of behaviors	Yang, Wen, Howley, Kraut, and Rose (2015)
BE	reply	This variable indicates how many threads a student initiated that have received a response from others. Student communication in the discussion forums is a vital component in MOOCs where personalized interaction is limited.	Yang, Wen, Howley, Kraut, and Rose (2015)

Latent construct	Metric	Definition	Study(ies) include
BE	topics	Topic l-Topic20: The numeric value of each topic variable represents the percentage of time during the time point (i.e., week of active participation) the student is identified by the model as participating in the associated subcommunity.	Yang, Wen, Kumar, Xing, and Rose (2014)
BE	total_number_of_this_week_lectures_viewed_online	Total number of this week lectures viewed online	Ye et al. (2015)
BE	total_number_of_this_week_lectures_downloaded	Total number of this week lectures downloaded	Ye et al. (2015)
BE	total_number_of_previous_week_lectures_viewed_online	Total number of previous week lectures viewed online	Ye et al. (2015)
BE	total_number_of_previous_week_lectures_downloaded	Total number of previous week lectures downloaded	Ye et al. (2015)
BE	total_number_of_next_week_lectures_viewed_online	Total number of next week lectures viewed online	Ye et al. (2015)
BE	total_number_of_next_week_lectures_downloaded	Total number of next week lectures downloaded	Ye et al. (2015)
BE	number_of_this_week_unique_lectures_viewed_online	Number of this week unique lectures viewed online	Ye et al. (2015)
BE	total_number_of_this_week_unique_lectures_downloaded	Number of this week unique lectures downloaded	Ye et al. (2015)
BE	total_number_of_previous_week_unique_lectures_viewed_online	Number of previous week unique lectures viewed online	Ye et al. (2015)
BE	total_number_of_previous_week_unique_lectures_downloaded	Number of previous week unique lectures downloaded	Ye et al. (2015)
BE	total_number_of_next_week_unique_lectures_viewed_online	Number of next week unique lectures viewed online	Ye et al. (2015)
BE	total_number_of_next_week_unique_lectures_downloaded	Number of next week unique lectures downloaded	Ye et al. (2015)
BE	average_number_thread_view_per_week	Average number of threads viewed, per week	Bergner et al. (2015)
BE	early_late_discussion_view_count	Represent two three-week intervals, which we label “early stage”—weeks 4-6, after the discussion forum had fully taken off but before the midterm—and “late stage”—weeks 9-11, after the midterm but before the final exam.	Bergner et al. (2015)
BE	lecture_video_views	Number of videos viewed	Brooks, Thompson, et al. (2015), Koedinger et al. (2015)
BE	discussion_forum_access	Frequency of discussion forum access	Brooks, Thompson, et al. (2015), Yu et al. (2015)
BE	number_of_unique_resources_accessed	Number of unique resources accessed	Champaign et al. (2014)



Latent construct	Metric	Definition	Study(ies) include
BE	login_count	Number of login events	Heutte et al. (2014)
BE	number_of_activities_engaged	Number of Activities Students Engaged in	Heutte et al. (2014)
BE	number_of_resources_visited	Number of Resources They Consulted	Heutte et al. (2014)
BE	activities_started	Number of OLI activities student started	Koedinger et al. (2015)
BE	pageview_count	Number of pageviews by a student	Koedinger et al. (2015)
BE	user_wiki_view	The number of times a learner has viewed wiki pages.	Vu et al. (2015)
BE	user_questions	The current number of questions that a learner has posted to the forum which measures her information seeking activity in the forum.	Vu et al. (2015)
BE	user_degree	The current number of threads to which a learner has posted which measures the breadth of her forum contributions.	Vu et al. (2015)
BE	user_degree_activity	The interaction between user_degree and user_activity which measures how the breadth of a learner's forum posts changes the effect of her contribution intensity, and vice versa.	Vu et al. (2015)
BE	user_forum_votes	The cumulative number of up votes subtracted by the cumulative of down votes on posts between a learner and a thread.	Vu et al. (2015)
BE	thread_view	The current number of view events on a thread weighted by their timestamps which is one of measurements for thread popularity.	Vu et al. (2015)
BE	degree_assortativity	The interaction between user degree and thread degree to test the assortativity in terms of node degrees.	Vu et al. (2015)
BE	activity_assortativity	The interaction between user activity and thread activity to test the assortativity in terms of node activities.	Vu et al. (2015)
BE	edge_view	The time-weighted cumulative number of view events from a learner to a thread.	Vu et al. (2015)
BE	edge_activity	The time-weighted cumulative number of post events from a learner to a thread.	Vu et al. (2015)
BE	target_language_in_media	Defined as either English or Spanish	Santos et al. (2014)
BE	social_network_degree	Social network degree in the first week, which measures the level of social integration. The social network degree measures the local centrality of learners in the online learning community. It is calculated as the number of edges to which the node is connected. In this study, authors treat learners as nodes and making comments to another learner's post is regarded as a directed edge from the commenter to the poster. The degree value is the number of connections that each learner has. Learners who did not participate in forums are assigned with 0 for their social network degree.	Jiang, Warschauer, Williams, O'Dowd, and Schenke (2014)

Latent construct	Metric	Definition	Study(ies) include
BE	degree centrality	The number of edges a node has in a network	Jiang, Fitzhugh, and Warschauer (2014)
BE	betweenness centrality	The number of shortest paths between any two nodes that pass via a given node	Jiang, Fitzhugh, and Warschauer (2014)
BE	closeness centrality	The distance of an individual node in the network from all the other nodes	Jiang, Fitzhugh, and Warschauer (2014)
BE	thread_degree	The current number of learners who have posted on a thread which is another measurement for thread popularity.	Vu et al. (2015)
BE	thread_activity	The time-weighted number of posts that a thread has received which measures the intensity of its popularity.	Vu et al. (2015)
BE	thread_degree-activity	The interaction between thread degree and thread activity statistics.	Vu et al. (2015)
BE	three-paths	The number of three paths from a learner to a thread that is used to test if learners tend to maintain their knowledge sharing collaborations over time.	Vu et al. (2015)
BE	three-paths_and_quiz_scores	An interaction between three-paths and quiz scores of learners on these paths to differentiate collaboration levels between low and high-performance learners.	Vu et al. (2015)
BE	edge_activity-three-paths	An interaction between edge activity and three-paths to control for the decrease of three-paths effect under the presence of previous posts.	Vu et al. (2015)
BE	edge_activity-three-paths_and_quiz_scores	An interaction between edge activity and three-paths and quiz scores to control for the decrease of three-paths and quiz scores effect under the presence of previous posts.	Vu et al. (2015)
BE	user_two-paths	The number of two paths from a learner that measures the popularity of discussion threads that she has engaged.	Vu et al. (2015)
BE	user_two-paths_and_quiz_scores	An interaction between user two-paths and quiz scores of learners on these paths.	Vu et al. (2015)
BE	thread_two-paths	The number of two paths from a thread that measures the breadth of forum contributions of learners who have engaged with it.	Vu et al. (2015)
BE	thread_two-paths_and_quiz_scores	An interaction between thread two-paths and quiz scores of learners on these paths.	Vu et al. (2015)
BE	user_post_recency	The gap time between the current time and the last post time to model the recency effect or the clustering of forum post activities.	Vu et al. (2015)
BE	thread_age	The gap time between the current time and the opened time of a thread. A negative coefficient implies the aging effect of discussion threads.	Vu et al. (2015)
BE	edge_forum_votes	The cumulative number of up votes subtracted by the cumulative of down votes on posts between a learner and a thread.	Vu et al. (2015)

Latent construct	Metric	Definition	Study(ies) include
BE	thread_forum_votes	The cumulative number of up votes subtracted by the cumulative of down votes on a thread.	Vu et al. (2015)
BE	forum_vote_assortativity	An interaction between user forum votes and thread forum votes to test the assortativity in terms of forum votes.	Vu et al. (2015)
<b>Affective engagement (AfFe)</b>			
AfFe	sentiments_expressed_in_forum	Sentiments, expressed within student posts/comments are weighted based on multiple factors such as the emoticon used to emphasize a textual sentiment (e.g., “I am very happy about my quiz grade : )”, a negative word that alter potentially positive sentiments (e.g., “I am not very happy about my quiz grade), etc. Since a single student post can express multiple sentiments, sentiment score bounds have theoretical bounds of $-\infty$ to $\infty$ .	Tucker et al. (2014)
AfFe	affective_processes	Linguistic Inquiry and Word Count (LIWC)* category	Yang, Wen, Howley, Kraut, and Rose (2015)
AfFe	positive_emotion	LIWC* category	Yang, Wen, Howley, Kraut, and Rose (2015)
AfFe	negative_emotion	LIWC* category	Yang, Wen, Howley, Kraut, and Rose (2015)
AfFe	polarity	predicate - calculated by normalizing the number of positive and negative polarity tags marked by opinion finder. This predicate takes values [0, 1].	Ramesh et al. (2014a), Ramesh et al. (2014b)
AfFe	subjectivity	predicate - calculated by normalizing the number of subjective/objective tags marked by opinion finder. This predicate takes values [0, 1].	Ramesh et al. (2014a), Ramesh et al. (2014b)
AfFe	expressed_confusion	This measures the average confusion per post a student has expressed in a week. It was calculated by averaging confusion scores of an individual's posts in a given week.	Yang, Wen, Howley, Kraut, and Rose (2015)
AfFe	user_exposed_confusion	This measures the average confusion per post a student was exposed to by averaging confusion scores of posts in the threads that student initiated during the time period.	Yang, Wen, Howley, Kraut, and Rose (2015)
AfFe	others_exposed_confusion	This measures the average confusion a student was exposed to by averaging the measured confusion of posts in all the threads he/she participated in those he/she initiated.	Yang, Wen, Howley, Kraut, and Rose (2015)
AfFe	confusion_resolved	This variable indicates how many threads are initiated by a student and are later resolved. Students sometimes express confusion through initiating threads with questions. Others providing satisfactory help to such threads might relieve the confusion of those students. Whether a thread was resolved or not is provided in the datasets.	Yang, Wen, Howley, Kraut, and Rose (2015)
AfFe	sentiment_assignments	The sentiment of the individual review for course assignments	Adamopoulos (2013)

Latent construct	Metric	Definition	Study(ies) include
AfFE	sentiment_professor	The sentiment of the individual review for the professor(s)	Adamopoulos (2013)
AfFE	sentiment_discussion_forum	The sentiment of the individual review for the discussion forum	Adamopoulos (2013)
AfFE	sentiment_course_material	The sentiment of the individual review for the course material	Adamopoulos (2013)
AfFE	positive_affect_panas	Positive affect, measured using Positive Affect and Negative Affect Scales (PANAS)	Heutte et al. (2014)
AfFE	negative_affect_panas	Negative affect, measured using Positive Affect and Negative Affect Scales (PANAS)	Heutte et al. (2014)
AfFE	course_sentiment_ratio	The sentiment ratio smoothed with one of the simplest possible temporal smoothing techniques, a moving average over a window of the past k days. The moving average of sentiment ratio Mat represents an estimation of collective opinion expressed by the students in the course forum during day t.	Wen, Yang, and Rosé (2014a)
AfFE	sentiment_towards_course_tools	For each course tool, the positive and negative sentiment words that associate most frequently with the course tool topic keywords were extracted. Finally, the sentiment words were ranked by the Pointwise Mutual Information (PMI) [16] between the word and the topic keyword.	Wen, Yang, and Rosé (2014a)
AfFE	individual_positivity	Average positivity in the user's posts that week	Wen, Yang, and Rosé (2014a)
AfFE	individual_negativity	Average negativity in the user's posts that week	Wen, Yang, and Rosé (2014a)
AfFE	thread_positivity	The average positivity a user was exposed to in a week. It was calculated by dividing the total number of positive words in the threads in a week where the user had posted by the total number of words in those threads.	Wen, Yang, and Rosé (2014a)
AfFE	thread_negativity	This variable measures the average negativity a user was exposed to in a week. It was calculated by dividing the total number of negative words in the threads in a week where the user had posted by the total number of words in those threads.	Wen, Yang, and Rosé (2014a)
<b>Cognitive engagement (CE)</b>			
CE	active	Active activities that show how students are actively engaged in the learning process.	Wang et al. (2015)
CE	constructive	Constructive activities that produce a representation of information that goes beyond the presented information	Wang et al. (2015)
CE	interactive	interactive activities that involve discussing and co-constructing with a peer or the learning environment	Wang et al. (2015)

Latent construct	Metric	Definition	Study(ies) include
CE	constructive_1	This is a binary variable indicating whether the student has a post that is categorized as "propose an idea/ ask novel questions".	Wang et al. (2015)
CE	constructive_2	This is a binary variable indicating whether the student has a post that is categorized as "Justify or provide reasons".	Wang et al. (2015)
CE	pronouns	LIWC* category	Yang, Wen, Howley, Kraut, and Rose (2015)
CE	negation	LIWC* category	Yang, Wen, Howley, Kraut, and Rose (2015)
CE	disfluencies	LIWC* category	Yang, Wen, Howley, Kraut, and Rose (2015)
CE	insight_words	LIWC* category	Yang, Wen, Howley, Kraut, and Rose (2015)
CE	assent	LIWC* category	Yang, Wen, Howley, Kraut, and Rose (2015)
CE	adverbs	LIWC* category	Yang, Wen, Howley, Kraut, and Rose (2015)
CE	certainty	LIWC* category	Yang, Wen, Howley, Kraut, and Rose (2015)
CE	discrepancy	LIWC* category	Yang, Wen, Howley, Kraut, and Rose (2015)
CE	question_features	LIWC* category	Yang, Wen, Howley, Kraut, and Rose (2015)
CE	narrativity_of_learner_aggregated_posts	Coh-Matrix** Narrativity principal component	Joksimović et al. (2015), Dowell et al. (2015)
CE	referential_cohesion_of_learner_aggregated_posts	Coh-Matrix** Referential cohesion principal component	Joksimović et al. (2015), Dowell et al. (2015)
CE	deep_cohesion_of_learner_aggregated_posts	Coh-Matrix** Deep cohesion principal component	Joksimović et al. (2015), Dowell et al. (2015)
CE	syntax_simplicity_of_learner_aggregated_posts	Coh-Matrix** Syntax simplicity principal component	Joksimović et al. (2015), Dowell et al. (2015)
CE	word_concreteness_of_learner_aggregated_posts	Coh-Matrix** Word concreteness principal component	Joksimović et al. (2015), Dowell et al. (2015)
CE	viewing_regularity_score	Those participants who typically watched or downloaded a video on the same day every week were regarded as showing evidence of planning, organization, self-discipline and reliability (i.e., conscientiousness). The modal day on which a person first watched a week's videos was identified (in the case of bi-modal or multi modal distributions, a single mode was chosen). An index of regularity was calculated, based on how often a person deviated from that modal day such that the most regular (those who always watched the video on the same day) scored 1, and those who had no identifiable modal day (i.e. they watched videos on a range of different days) scored 0, with others scoring between 0 and 1.	Loya et al. (2015)
	average_cognitive_engagement	This variable measures the average abstractness score per post each week	Wen, Yang, and Rose (2014b)
CE	essay_score_algorithm	Writing Assessment Tool (WAT) score	Crossley et al. (2015)

Latent construct	Metric	Definition	Study(ies) include
CE	type_token_ratio	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	number_of_word_types	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	average_post_length	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	concreteness	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	cardinal_numbers	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	trigram_frequency	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	bigram_frequency	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	number_of_sentences	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	frequency_content_words	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	situational_cohesion	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	hypernymy_standard_deviation	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	word_meaningfulness	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	lexical_diversity	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	average_word_length	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	essay_body_quality_algorithm	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	logical_connectors	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	word_age_of_acquisition	WAT, TAALES, or TAAS*** indices	Crossley et al. (2015)
CE	cognitive_absorption_eduflow	Feeling in control of the activity one is in as a result of knowing that the activity is doable and that one's skills are adequate, producing no anxiety nor boredom	Heutte et al. (2014)
CE	altered_perception_of_time_eduflow	Feeling of timeliness which is the result of being intensely focused on one's present activity	Heutte et al. (2014)
CE	loss_of_self-consciousness_eduflow	Not being concerned with oneself	Heutte et al. (2014)
CE	well-being_eduflow	Being outside of daily reality to a degree that one feels ecstatic	Heutte et al. (2014)
<b>Contextual (demographics) (CD)</b>			
CD	age	Age	Konstan et al. (2015), Kizilcec and Halawa (2015), Engle et al. (2015), Heutte et al. (2014), Koedinger et al. (2015), Greene et al. (2015)
CD	years_of_education	Years of formal education	Konstan et al. (2015)
CD	country_of_origin	Country of origin	Konstan et al. (2015), Heutte et al. (2014)
CD	gender	Gender	Konstan et al. (2015), Kizilcec and Halawa (2015), Adamopoulos (2013), Heutte et al. (2014), Koedinger et al. (2015)
CD	english_proficiency	English proficiency	Konstan et al. (2015)
CD	usa_residency	USA residency	Konstan et al. (2015)

Latent construct	Metric	Definition	Study(ies) include
CD	introversion_extroversion	Introversion/Extroversion	Konstan et al. (2015)
CD	english_native_language	English native language	Konstan et al. (2015)
CD	number_of_concurrent_courses	Number of concurrent courses currently enrolled in	Konstan et al. (2015)
CD	education_bachelor+	Whether student has bachelor degree or higher	Konstan et al. (2015)
CD	prior_experience	Prior experience with MOOCs	Konstan et al. (2015)
CD	hours_dedicated_2_to_4_dummy	Binary variable indicating whether student aimed to dedicate 2 to 4 hours per week	Kizilcec and Halawa (2015)
CD	hours_dedicated_4+_dummy	Binary variable indicating whether student aimed to spend more than 4 hours per week	Kizilcec and Halawa (2015)
CD	prior_moocs_1_to_3_dummy	Binary variable indicating whether student completed 1 to 3 courses	Kizilcec and Halawa (2015)
CD	prior_moocs_4+_dummy	Binary variable indicating whether student completed more than 4 courses	Kizilcec and Halawa (2015)
CD	location_europe_dummy	Binary variable indicating whether student is located in Europe	Kizilcec and Halawa (2015)
CD	location_oceania_dummy	Binary variable indicating whether student is located in Oceania	Kizilcec and Halawa (2015)
CD	location_africa_dummy	Binary variable indicating whether student is located in Africa	Kizilcec and Halawa (2015)
CD	location_asia_dummy	Binary variable indicating whether student is located in Asia	Kizilcec and Halawa (2015)
CD	location_latin_america_dummy	Binary variable indicating whether student is located in Latin America	Kizilcec and Halawa (2015)
CD	programming_skills_confidence	Programming skills confidence	Konstan et al. (2015)
CD	professional_previous_experience_dummy	Professional experience	Konstan et al. (2015)
CD	graduate_student_previous_experience_dummy	Graduate student	Konstan et al. (2015)
CD	undergraduate_student_previous_experience_dummy	Undergraduate student	Konstan et al. (2015)
CD	number_of_programming_courses_taken	Number of programming courses taken prior to the given course	Konstan et al. (2015)
CD	other_moocs_prev_taken	Binary variable indicating whether student has enrolled MOOCs before	Konstan et al. (2015)
CD	matriculated_student	Binary variable indicating whether the student attends a formal educational institution	Adamopoulos (2013)
CD	race	Race	Brooks, Thompson, et al. (2015)
CD	language_capabilities	Language capabilities	Brooks, Thompson, et al. (2015)
CD	state	State (location)	Brooks, Thompson, et al. (2015)
CD	city	City (location)	Brooks, Thompson, et al. (2015)
CD	level_of_education	The highest level of education completed	Goldberg et al. (2015), Greene et al. (2015), Engle et al. (2015), Heutte et al. (2014), Koedinger et al. (2015), Konstan et al. (2015), Kizilcec and Halawa (2015), Adamopoulos (2013)

Latent construct	Metric	Definition	Study(ies) include
CD	academic_background	Academic background	Greene et al. (2015), Engle et al. (2015)
CD	previous_experience	Previous experience with the course's subject area.	Greene et al. (2015), Engle et al. (2015)
CD	mooc_completion	Completed/Not completed MOOC	Goldberg et al. (2015)
CD	current_job_related_to_MOOC_topic	Binary variable indicating whether student's current job is related to the course topic	Greene et al. (2015)
CD	current_academic_program_related_to_MOOC_topic	Binary variable indicating whether student's current academic program is related to the MOOC topic	Greene et al. (2015)
CD	work_experience_in_MOOC_topic	Binary variable indicating whether student has work experience in a field related to the MOOC topic	Greene et al. (2015)
CD	MOOC_topic_helpful_in_obtaining_a_job	Binary variable indicating whether student considers MOOC important for obtaining a job	Greene et al. (2015)
CD	prior_experience_w_MOOCs	Binary variable indicating student's prior experience with MOOCs	Greene et al. (2015), Konstan et al. (2015)
CD	prior_experience_w_Coursera	Binary variable indicating student's prior experience with Coursera	Greene et al. (2015)
CD	currently_enrolled_in_another_MOOC	Binary variable indicating whether student is currently enrolled with another MOOC	Greene et al. (2015)
CD	student_or_professional_status	ICT related profession, education related profession, retirement, leave for training, part-time	Heutte et al. (2014)
CD	uci_undeclared_major	Whether or not a learner is an incoming UCI Undeclared major student	Jiang, et al. (2014)
CD	instructional_group	Whether student was MOOC only or MOOC+OLI	Koedinger et al. (2015)
<b>Contextual (classroom) (CC)</b>			
CC	programming_vs_concepts_track	Programming vs. conceptual track selected in the course	Konstan et al. (2015)
CC	number_of_students_known	Number of students known	Konstan et al. (2015)
CC	the_absolute_time_since_course_start	The absolute time (in days, since course start) t	Whitehill, et al. (2015)
CC	course_self-paced	Whether the course is self-paced (dummy)	Adamopoulos (2013)
CC	course_difficulty	The average difficulty of the course	Adamopoulos (2013)
CC	course_workload	The estimated workload in hours/week	Adamopoulos (2013)
CC	course_num_weeks	Duration of the course in weeks	Adamopoulos (2013)
CC	course_certificate	Whether students who successfully complete the course receive a certificate (dummy)	Adamopoulos (2013)
CC	course_peer-assessments	Whether there is peer assessment in the course (dummy)	Adamopoulos (2013)
CC	course_team_projects	Whether there is any team project in the course (dummy)	Adamopoulos (2013)
CC	course_suggested_textbook	Whether there is a suggested textbook (dummy)	Adamopoulos (2013)
CC	course_suggested_paid_textbook	Whether there is a suggested paid textbook (dummy)	Adamopoulos (2013)
CC	course_final_exam-project	Whether there is a final exam or project in the course (dummy)	Adamopoulos (2013)
CC	course_university_ranking	Relative ranking of the university	Adamopoulos (2013)



Latent construct	Metric	Definition	Study(ies) include
CC	course_courses_offered	The number of courses offered by the university	Adamopoulos (2013)
CC	course_business_and_management	Whether the course belongs to the Business & Management discipline (dummy)	Adamopoulos (2013)
CC	course_computer_science	Whether the course belongs to the Computer Science discipline (dummy)	Adamopoulos (2013)
CC	course_engineering	Whether the course belongs to the Engineering discipline (dummy)	Adamopoulos (2013)
CC	course_humanities	Whether the course belongs to the Humanities discipline (dummy)	Adamopoulos (2013)
CC	course_mathematics	Whether the course belongs to the Mathematics discipline (dummy)	Adamopoulos (2013)
CC	course_science	Whether the course belongs to the Science discipline (dummy)	Adamopoulos (2013)
CC	platform_canvas_network	Whether the course is offered on the Canvas Network platform (dummy)	Adamopoulos (2013)
CC	platform_udacity	Whether the course is offered on the Udacity platform (dummy)	Adamopoulos (2013)
CC	platform_venture_lab	Whether the course is offered on the Venture Lab platform (dummy)	Adamopoulos (2013)
CC	platform_coursera	Whether the course is offered on the Coursera platform (dummy)	Adamopoulos (2013)
CC	platform_edx	Whether the course is offered on the edX platform (dummy)	Adamopoulos (2013)
CC	platform_codecademy	Whether the course is offered on the Codecademy platform (dummy)	Adamopoulos (2013)
CC	friends	Whether students enrolled with their friends or alone	Brooks, Stalburg, Dillahunt, and Robert (2015)
CC	signature_track	Binary variable indicating whether a student enrolled free or payed version of the course	Brooks, Thompson, et al. (2015)
CC	signup_date	Signup date	Brooks, Thompson, et al. (2015)
<b>Contextual (motivation) (CM)</b>			
CM	intent_to_complete	intention_to_complete_course, commitment_to_earning_certificate	Konstan et al. (2015), Kizilcec and Halawa (2015), Greene et al. (2015)
CM	professional_reasons_dummy	Binary variable indicating whether student enrolled a course because of professional reasons	Konstan et al. (2015)
CM	university_instructor_reasons_dummy	Binary variable indicating whether student enrolled a course because of the university instructor	Konstan et al. (2015)
CM	interest_enjoyment_reasons_dummy	Binary variable indicating whether student enrolled a course because of personal interests/enjoy	Konstan et al. (2015)
CM	pragmatic_access_reasons_dummy	Binary variable indicating whether student enrolled a course because of pragmatic access	Konstan et al. (2015)
CM	plans_to_complete	Binary variable indicating whether student planned to complete	Konstan et al. (2015)
CM	average_motivation	The percentage of an individual's posts in that week that are predicted as "motivated" using the built model	(Wen, Yang, & Rose, 2014b)

Latent construct	Metric	Definition	Study(ies) include
CM	motivation_heuristic_attempts	Motivation estimated using heuristic filters on attempts	Bergner et al. (2015)
CM	motivation_heuristic_time	Motivation estimated using heuristic filters on time	Bergner et al. (2015)
CM	motivation_aoe	Motivation estimated using latent class analysis of AOE	Bergner et al. (2015)
CM	intentions	Student intention	Engle et al. (2015)
CM	hours_intention	Number of hours intended to devote to the course work	Konstan et al. (2015), Engle et al. (2015), Heutte et al. (2014), Kizileec and Halawa (2015), Greene et al. (2015)
CM	intention_to_earn_certificate	Intention to earn a certificate	Greene et al. (2015)
CM	general_interest_in_MOOC	General interests in MOOCs	Greene et al. (2015)
CM	implicit_theory_of_intelligence_score	Intelligence score estimated using implicit theory	Greene et al. (2015)
CM	reason_to_dropout	Reason to dropout	Heutte et al. (2014)
CM	general_interest_in_topic	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	relevant_to_job	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	relevant_to_school_or_degree_program	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	relevant_to_academic_research	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	for_personal_growth_and_enrichment	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	for_career_change	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	for_fun_and_challenge	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	to_meet_new_people	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	to_experience_an_online_course	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	to_earn_a_certificate-statement_of_accomplishment	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	course_offered_by_prestigious_university-professor	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	to_take_with_colleagues-friends	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)
CM	to_improve_my_English_skills	Score calculated using Online Learning Enrollment Intentions scale	Kizileec and Schneider (2015)

\* <http://liwc.wpengine.com/>

\*\* <http://colmetrix.com/>

\*\*\* WAT – Writing Assessment Tool, TAALES – Tool for the Automatic Analysis of Lexical Sophistication, TAAS – Tool for the Automatic Assessment of Sentiment